Morality, Social Identity and Environmentally Conscious Economic Behaviour: Advancing our Understanding of Green Consumption and Investment

NAGA, LUCY,VICTORIA

Morality, Social Identity and Environmentally Conscious Economic Behaviour: Advancing our Understanding of Green Consumption and Investment

A thesis submitted in partial fulfilment of the

Requirements for the degree of

Doctor of Philosophy

Lucy Victoria Naga

Department of Economics

Durham University

2025

Morality, Social Identity and Environmentally Conscious Economic Behaviour: Advancing our Understanding of Green Consumption and Investment.

Lucy Victoria Naga

Abstract

The neoclassical framework of independent, self-interested, utility-maximising agents often fails to adequately explain environmentally sustainable behaviours. This thesis explores how integrating key aspects of human nature — such as morality and social identity — into economic models can better capture the drivers of sustainable decision-making.

In the first two papers, I develop theoretical models to examine the influence of Kantian morality on consumer and investor behaviour. The first paper investigates consumer behaviour within an optimal taxation framework. It demonstrates that in a homogeneous society of perfectly moral agents, environmental externalities are fully internalised, eliminating the need for corrective taxation. However, heterogeneity in preferences and income can reduce the degree of internalisation, necessitating government intervention. The second paper analyses investor behaviour using a two-period asset pricing model. It shows that in an economy composed entirely of Kantian investors, the price premium on polluting assets equals to social cost of their externalities. When a proportion of investors deviate from Kantian principles to optimise in a self-interested manner, moral investors partially compensate for excessive investment in polluting assets but fail to achieve a Pareto optimal outcome.

The final paper presents an empirical study of household preferences for renewable heating systems, exploring the role of latent environmental attitudes, energy attitudes, and social identity in shaping willingness to pay for heating system attributes. The estimation results reveal that pro-environmental attitudes, energy-saving attitudes, and coal mining identity significantly influence how households prioritise the different social benefits arising from the heating systems. Whilst predicted effects of latent variables on sensitivity to attributes are of the expected sign, the effects on willingness to pay are limited due to cost sensitivity. Investment cost emerges as a critical factor in the attitude-behaviour gap.

Contents

List of Tables

List of Figures

Declaration

The work described in this thesis was undertaken in the Department of Economics at Durham University (UK) between October 2021 and November 2024, under the supervision of Professor Laura Marsiliani of Durham University and Dr Thomas Renström of Durham University. This work has not been previously submitted for a degree at this or any other university.

Chapter 1 is based on a joint research paper with Prof. Laura Marsiliani and Dr Thomas Renström. All authors contributed to the concept development of the paper. I was heavily or solely responsible for the literature review, the model proof and the model extension to heterogeneous consumers.

Chapter 2 is based on a joint research paper with Prof. Laura Marsiliani and Dr Thomas Renström. All authors contributed to the paper. I was heavily or solely responsible for the literature review, the model proof, the model extension to partially Kantian economies, and the simulation.

Chapter 3 is based on a joint research paper with Kalila Mackenzie, Prof. Laura Marsiliani, Dr Jingyuan Di, Dr Thomas Renström and Prof. Ricardo Scarpa. All authors contributed significantly to the design and drafting of this project. I was heavily or solely responsible for the literature review, the behavioural aspects of the survey, the data cleaning, the choice modelling and analysis, and the policy simulations.

Statement of Copyright

Funding

This work was funded by Durham University Business School (DUBS) Scholarship.

Chapter 3 was part of the WP3 of the Geothermal Energy from Mines and Solar-Geothermal Heat (GEMS) project funded by the United Kingdom Research Council (UKRI) / Engineering and Physical Sciences Council (EPSRC).

The survey in chapter 3 was funded by the DUBS Faculty Primary Research Support Fund.

Publications

Marsiliani, L., Naga, L., Renström, T.I., Spararo, L., (2023) "Theory of Socially Responsible Investment: A Review.", Assessing the EU Strategy on Green Finance and ESG Factors: An Interdisciplinary Approach, edited by Spataro, L., Quirici, M.C., Iermano, G., Palgrave Macmillan (Springer). https://doi.org/10.1007/978-3-031-36457-0_2

Acknowledgements

I would like to thank my supervisors Prof. Laura Marsiliani and Dr Thomas Renström for their guidance and support throughout my PhD. I would also like to thank Dr Leslie Reinhorn and Prof. Ricardo Scarpa for their constructive feedback and helpful advice.

I never meant to study economics. Truth be told, I never really knew what the subject was when I was growing up. But when I was awarded the Bernard Drake Scholarship in Economics to study my A-levels at Eastbourne College, I thought perhaps I would be pretty good at it. Turning up to my first economics class in year 12, I felt like I was seeing the world from a whole new angle. Suddenly so much made sense, suddenly I had so many more questions. I would like to thank Douglas Fergusson for funding my scholarship and giving me this opportunity.

Not quite ready to commit purely to economics, I studied Philosophy, Politics and Economics at the University of Oxford. I spent half of my time in a rowing boat and the other half bending my mind around philosophical theories that I feel I am still yet to grasp. Economics was the relaxing part of my day, solving equations and applying theories. I would like to thank Dr Richard Povey for his clear and engaging tutorials and for supporting my subsequent progress.

My inspiration to study a PhD in Economics comes from my MSc in Development Economics. The more that you learn, the more questions you have, however, the more that you know, the less likely it is that someone has answered your question. This is where research begins. I would like to thank Prof. Andy McKay for supervising my dissertation and introducing me to the world of research.

As I submit these pages, perhaps I can now say that I am an economist. I am incredibly proud of what I have achieved and incredibly thankful for all the teachers and mentors who have shaped my journey.

Finally, I would like to thank my family for their love and encouragement. My Mum and Dad for always believing in me, my sister for being my biggest cheerleader, and my brother for being a voice of reason. I thank my husband for celebrating the highs and supporting me through the lows, I thank him for creative dinner time conversations and whiteboard maths derivations, I thank him for his patience and serenity.

CHAPTER 0: Motivation

Lucy Naga

Within economics, the environmental dilemma can be represented in the form of two key market failures. Firstly, the degradation of the environment is a classic example of an externality. Externalities arise when the social costs and benefits of an action do not match the private costs and benefits that are accounted for by the decision-makers. Within the environmental dilemma, decision-makers fail to account for the external effects of their actions on the environment and on the well-being of others. This results in low market prices, overconsumption of harmful goods, and excessive environmental damage. Secondly, the failure to adequately protect the environment is an example of a public goods dilemma. Everyone stands to gain from a healthy environment. These gains are non-excludible and non-rivalrous. No one can be prevented from deriving benefits from environmental quality, and these benefits are independent of the number of others also benefiting from it. This allows for an individual to free ride on others' contributions to environmental quality, making it individually irrational for them to contribute. These two market failures present a key challenge for international and national policy to encourage environmentally conscientious behaviour by firms, investors, and consumers.

Despite the pessimism emanating from the economics discipline, considerable hope can be found when we look to human nature and the intrinsic motivations behind human action. A consumer survey by Deloitte (2023) highlighted that a significant proportion of consumers purposefully engage in sustainable behaviours. They find that 76% of people invest additional effort to recycle their waste, 42% of people pay more for durable or long-lasting products, and 36% of people spend time fixing or repairing items rather than replacing them with equivalent items. Meanwhile, a record $649 billion flowed into Environmental, Social and Governance funds worldwide in 2021, up from $542 billion and $285 billion in 2020 and 2019 (Reuters, 2021). Each of these behaviours contradicts conventional economic theory. Here, many respondents are incurring additional private costs to the benefit of society at large, even when they derive negligible material benefits from their own contributions. When questioned why they are environmentally sustainable, many people refer to the value they place upon the environment and on the wellbeing of others, or to wanting to do their part or to do the right thing. This suggests that the nexus of care expands beyond the individual themselves and that the consideration of actions expands beyond expected consequences.

Social psychology theories of behaviour such as the Behavioural Reasoning Theory (BRT, Westaby, 2005; Claudy *et al.*, 2013), and the Value-Belief-Norm framework (VBN, Stern *et al.,* 1995, 1999) emphasise the key role of social structures, worldviews, values, beliefs, and norms. Our experiences and our social environment shape how we see the world and what holds value, whilst social rules and moral norms determine codes of conduct and set ethical standards. Many economic behaviours are performed in this rich setting and thus are guided by our social identity and moral ideals.

DEFRA's 2021 (Department for Environment Food and Rural Affairs, 2021, Section 3.2 'Behavioural and Social Science') Research and Innovation Report highlighted the importance of this research agenda by posing the following questions, 'How can we encourage or incentivise behavioural change among businesses, communities, and individuals to achieve positive outcomes for the environment? What models of societal change might be used to underpin these behaviour-change initiatives?'. Understanding human behaviour is key to designing effective policies. Policies impose external incentives aiming to bring the competitive equilibrium of the economy closer to the Pareto optimal allocation where social welfare is optimised; however, the influence of external incentives is contingent upon the extant internal motivations of humans (Frey and Stutzer, 2006). To fully understand human behaviour it is necessary to deviate from Edgeworth's 'rational fool' (Sen, 1977), taking on the mantle from Adam Smith (1759, Part 3, Ch1, p 129) to 'thoroughly enter into all the passions and motives which influenced it'.

Within my thesis, I explore how we can model environmentally sustainable behaviours by drawing on the moral and social motivations of economic agents. Within my first two papers, I focus on the role of morality, modelling economic agents to optimise their behaviour according to Kant's (1785, as in Koorsgaard, 2012) categorical imperative,

"Act only according to that maxim whereby you can, at the same time, will that it should become a universal moral law".

(Kant, 1785, 4:421 as in Koorsgaard 2012, p34).

This can be interpreted as setting out a logical relation that one should only engage in an action if one can consistently wish that others do the same thing if they were in the same situation. Thus, rather than seek to maximise their own gain assuming *ceteris paribus*, the Kantian agent would seek to do the 'right thing', whereby they consider the hypothetical outcome of everyone doing the same as themselves. Throughout my thesis, I employ Roemer's (2010) formalisation of Kantian morality, whereby the 'same maxim' is interpreted as the same deviation from current consumption or investment. This interpretation facilitates greater flexibility and allows for investigation into the effects of heterogeneity.

Within my first paper, I employ Roemer's (2010) formalisation of Kantian moral preferences to model how green consumers optimise their consumption of dirty goods with negative consumption externalities. I incorporate these enriched consumer preferences into the Ramsey model of second-best commodity taxation, introducing both clean and dirty goods, to investigate how optimal consumption taxation policy changes in the presence of moral consumers. I investigate the case of both homogeneous and heterogeneous moral agents. My results demonstrate that when consumers with homogeneous preferences and incomes optimise in a Kantian moral manner, they voluntarily internalise environmental externalities, removing the need for Pigouvian taxation and resulting in the Ramsey Rule holding. Furthermore, I find that morality increases the inelasticity of demand for dirty goods, resulting in a higher optimal Ramsey taxation for dirty goods relative to clean goods. When I expand my model to consider moral agents with heterogeneous preferences and incomes, I find that the externality is only partially internalised. The residual externality and hence the optimal Pigouvian taxation depends upon the variance of preferences and the correlation between preferences and income.

Within my second paper, I employ a similar framework of moral optimisation to model how green investors optimise their portfolios of clean and dirty assets. I build a two-period asset pricing model and derive the asset pricing relation (1) under Pareto optimality, (2) in a competitive non-Kantian economy, (3) in a competitive Kantian economy, (4) in a competitive partial Kantian economy with exclusive Kantian investors and non-Kantian investors, (5) in a competitive partial Kantian economy with inclusive Kantian investors and non-Kantian investors. Under Pareto optimality, the return on dirty assets must be higher to compensate for the marginal social costs arising from the dirty firm's pollution externalities. This pollution premium increases the costs of production for the dirty firm and thus reduces pollution to optimal levels. In a competitive non-Kantian economy, individual investors do not take into account pollution externalities, and thus the return is equalised across clean and dirty assets, resulting in over-investment in the dirty firm and sub-optimally high levels of pollution.

In a competitive Kantian economy, each Kantian investor considers the pollution damages they would suffer if all investors were to increase their investment in the dirty firm and thus seeks to reduce their own investment to reduce this cost. In each of the partially Kantian economies, non-Kantian investors would invest solely in dirty assets until their return is equalised with clean assets. Meanwhile, when Kantians are exclusive, they would take into account the behaviour of non-Kantians and consider the pollution damages they would suffer given current levels of non-Kantian investment if only Kantian agents increased their investment. We find that in a partially exclusive Kantian economy, the pollution premium declines and the overall level of dirty investment rises with the proportion of non-Kantians. When Kantians are inclusive, they would consider the pollution damages if both Kantians and non-Kantians were to increase their investment, even though non-Kantians optimise differently. We find that in a partially inclusive Kantian economy, the same trends will hold as in the partially exclusive Kantian economy. We find that inclusive Kantians invest more in dirty assets than exclusive Kantians. We analytically derive our results and run simulations to demonstrate how Kantian and non-Kantian portfolios change as the proportion of non-Kantians in the economy increases.

Within my third paper, I conduct a discrete choice experiment to investigate household stated preferences for renewable heating technologies and the behavioural determinants of household investment decisions. This study is part of a project on geothermal energy from disused mines, where we are investigating household perception and willingness to pay for new technologies. We conducted a household survey within which we conducted our choice experiment and collected behavioural data on attitudes and perceptions as well as socio-demographic data. The choice experiment established the hypothetical scenario of purchasing a heating system for a new property, it included four renewable heating technologies: geothermal district heating, hydrogen boiler, solar electric boiler, and air source heat pump. Each technology was described by five attributes: investment cost, monthly cost, replacement period, annual CO2 emissions, and job creation.

I use data from this survey to analyse how latent variables of pro-environmental attitudes, energy-saving attitudes, and coal-mining social identity influence household stated preferences for renewable heating systems. I employ an integrated choice latent variable (ICLV) model to investigate how these latent variables influence sensitivity towards different heating system attributes, how this translates into willingness to pay, and how such attitudes may influence responsiveness to policy changes. I find that both pro-environmental and energy-saving attitudes increase sensitivity towards CO2 emissions. I also find that those who are more pro-environmental are less sensitive to cost, and thus overall have a higher willingness to pay for cleaner heating systems. On the other hand, those who are more energy-conscious have a higher sensitivity to cost, and thus overall do not have a higher willingness to pay for cleaner heating systems. Meanwhile, those who identify more strongly with the coal mining heritage of the region are more likely to choose geothermal heating systems and have a higher sensitivity to job creation, but their heightened sensitivity to cost means they are not willing to pay more for heating systems that create more jobs. Our policy simulations demonstrate that if a carbon price is introduced, demand will shift towards cleaner heating systems, with demand being more elastic for energy-conscious households and less elastic for pro-environmental households.

Overall, this thesis demonstrates the power of intrinsic motivation in driving sustainable behaviours. It demonstrates that conventional economics is too pessimistic about human nature and that morality, social norms, and cultural identity play important roles in the decision-making of economic agents. This highlights the need for policy to consider how conventional economic incentives interact with intrinsic motivations to ensure that they crowd in such motivations rather than crowding them out.

CHAPTER 1: Kantian Morality and Optimal Second-Best Commodity Taxation

Lucy Naga*, Thomas Renström, Laura Marsiliani

Abstract

When investigating optimal taxation in the presence of green consumerism, economists largely focus on corrective Pigouvian taxation within partial equilibrium models in a first-best world. Depending upon the operationalisation of green preferences, studies find that optimal corrective Pigouvian taxes reduce or stay constant. In this paper, we build upon the Ramsey optimal commodity taxation structure (Ramsey, 1927) in a second-best world to investigate how moral green preferences influence optimal Pigouvian corrective taxation and Ramsey revenue-raising taxation for goods with environmental externalities. We employ Roemer's (2010) formalisation of Kantian moral preferences to model how green consumers optimise their consumption of dirty goods. We incorporate these enriched consumer preferences within the Ramsey model, introducing both dirty and clean goods. We investigate the case of both homogeneous and heterogeneous moral agents. Our results demonstrate that when consumers with homogeneous preferences and incomes optimise in a Kantian moral manner, consumers voluntarily internalise environmental externalities, removing the need for Pigouvian taxation and resulting in the Ramsey Rule holding. Furthermore, morality reduces the elasticity of demand for dirty goods, resulting in a higher optimal Ramsey taxation for dirty goods relative to clean goods. When we expand our model to consider moral agents with heterogeneous preferences and incomes, we find that the externality is only partially internalised. The residual externality and hence the optimal Pigouvian taxation depends upon the variance of preferences and the correlation between preferences and income.

JEL classification: D62, D91, H21, Q58.

Keywords: Optimal taxation, Pigouvian taxation, Environmental externality, Green consumerism, Kantian morality.

Acknowledgements: We would like to thank Leslie Reinhorn and Riccardo Scarpa for their insightful comments. Karine Nyborg and the participants of the EAERE 'Summer School of Economic Foundations of Energy and Climate Policies' Florence, 19-23 September 2022, participants of the FSR Climate virtual Annual Conference 1-2 December 2022, and participants of the EPCS Annual Conference 22-25 March 2023.

*Corresponding author: Lucy Naga, Department of Economics Durham University Business School, Mill Hill Lane, Durham DH1 3LB, United Kingdom. Email: lucy.v.hyde@durham.ac.uk
Laura Marsiliani, Department of Economics Durham University Business School, Durham Energy Institute and Durham Centre for Sustainable Development, Law and Policy, Mill Hill Lane, Durham DH1 3LB, United Kingdom. Email: laura.marsiliani@durham.ac.uk
Thomas I. Renström, Department of Economics Durham University Business School, Mill Hill Lane, Durham DH1 3LB, United Kingdom. Email: t.i.renstrom@durham.ac.uk

1.1 Introduction and Context

'Every economic action takes place in the framework of a moral or ethics'

(Laffont, 1975, p.431)

When consumption behaviour exhibits externalities, ethical enquiry is a relevant consideration for economic agents. Ethical economic agents may apply moral principles to evaluate the 'right' action given the available alternatives, payoffs, and consequent externalities. Philosophy provides a plethora of moral principles. Economists tend to adopt egoistic consequentialism, whereby agents seek to maximise their own material gain. However, within a deeply interconnected and interdependent society, a richer concept of 'rightness' is necessary. On the one hand, egoistic consequentialism may be expanded to utilitarianism, whereby a universal, altruistic form of consequentialism is applied to maximise the material payoff for the greatest number of agents. However, this demands considerable knowledge of the welfare of others and may be criticised as asking too much. On the other hand, consequentialism may be abandoned for deontological moral principles, whereby agents employ moral rules to guide their behaviour. Kant's categorical imperative provides a golden rule for evaluating behaviour. It states that one should,

"Act only according to that maxim whereby you can, at the same time, will that it should become a universal law".

(Kant, 1785, 4:421 as in Koorsgaard, 2012, p34)

This can be interpreted as setting out a logical relation that an individual should only engage in a behaviour if they can consistently wish that all others do the same thing if they were in a similar situation. Kantian morality has been employed within the context of economics to explain voluntary contributions to public goods (Laffont, 1975; Brekke *et al*., 2003; Roemer, 2010) and may be applied to broader contexts to explain voluntary internalisation of external effects. Within the framework of Kantian reasoning, economic agents are modelled to internalise the externalities arising from their own actions by seeking to reduce the externalities imposed upon them by other agents. This echoes the Christian doctrine, 'do to others what you would have them do to you' (Matthew 7:12, New International Version).

In the context of environmental economics, moral preferences can be used to model the behaviour of green consumers. Green consumers have an awareness of the environmental consequences of their consumption decisions and actively seek to internalise the negative environmental externalities which arise from production processes, consumer usage and final disposal methods (Ottman, 1992). Neoclassical models of consumer behaviour adopt egoistic preferences, failing to capture patterns of green consumerism since agents disregard the external effects of their actions. Economists have sought to model green consumerism in various ways. Ambec and DeDonder (2022) employ Andreoni's (1989, 1990) concept of a 'warm glow', modelling green consumers to derive a private benefit from contributing to environmental sustainability. This warm glow could stem from a personal desire to contribute to the environment. It could be embedded in social preferences such as altruism (Andreoni, 1990), network effects (Brécard, 2013; Nyborg, 2020), social norms (Nyborg, 2018; Dasgupta *et al.,* 2016), or social reputation (Rege, 2004; Kassab, 2020), and could be influenced by moral convictions to do the 'right thing' (Laffont, 1975; Brekke *et al.,* 2003; Roemer, 2010; Alger and Weibull, 2013).

Within this paper, we will focus on the Kantian moral foundations of green consumerism. Laffont (1975) introduced Kantian morality into the economics literature, employing Kant's categorical imperative to explain why beachgoers do not leave their beer cans on the beach. The moral individual contemplates what the right behaviour is by considering how they would like it if all other individuals did likewise. Whilst leaving their own beer can on the beach causes them negligible aesthetic costs, if all others did the same, the cost would be significant, thereby outweighing the cost of the effort employed to dispose of their beer can. Thus, the Kantian would contribute to the public good of a clean beach and dispose of their beer can. This form of reasoning is relevant whenever externalities arise from an individual's actions. It is particularly pertinent in the context of atmospheric externalities, where the individual's action has a negligible effect. For, in this case, even when the individual cares about the environment or cares about the wellbeing of others, their action does not pose sufficient costs upon these ends to motivate a behaviour change. It is also particularly relevant in the context of unobserved externalities, whereby an agent's action or the externalities arising from it are not common knowledge, for in this case social norms and reputation would have weaker influences upon agent behaviour. Henceforth, the internal moral motivations of agents are an important consideration in the context of green consumerism, whereby individual consumers have negligible and potentially unobservable effects on the environment.

Alger and Weibull (2013, 2016) investigate whether the theory of Kantian motivation is evolutionarily conceivable for economic agents. They employ evolutionary game theory based on survival-of-the-fittest logic, modelling agent-agent interactions whereby preferences guide the behaviour of agents, behaviour generates fitness payoffs, and fitness payoffs determine the distribution of preferences for future generations. They argue that a degree of Kantian morality can be sustained in the general population if assortative matching is incorporated into the model. Assortative matching allows for homophilic tendencies to increase the likelihood of individuals interacting with others of the same type. Henceforth, whilst neoclassical Nashian agents would outperform Kantian agents in one-on-one interactions through free-riding off the Kantian's efforts, Kantian-Kantian interactions bring sufficiently higher payoffs to sustain the survival of such moral preferences.

Miettinen *et al.* (2020) and Van Leeuwen and Alger (2021) empirically investigate whether individuals display Kantian preferences. They run a series of experimental games to explore how well different formulations of utility functions represent individual behaviour within strategic interactions. Both papers find evidence of moral behaviour in conjunction with both selfish and other-regarding or social preferences. They find that including morality improved how well their model fits observed behavioural patterns.

Within the theoretical literature, economists have integrated moral preferences into the utility function of economic agents in several different ways. For homogeneous agents, Kantian moral preferences lead identical individuals to consider their utility given the hypothetical scenario that all other agents perform the same action as themselves. A fully Kantian consumer would therefore consume the quantity that they would be happy for all individuals to consume. A partially Kantian agent might consider their material and moral preferences separately, trading off the material gain from higher consumption of a dirty good against the moral gain from lower consumption (Alger and Weibull, 2013, 2016; Eichner and Pethig, 2022; Ayoubi and Thurm, 2020). Alternatively, a partially Kantian agent may relate morality to a self-image payoff, whereby they derive positive utility from consuming close to their Kantian moral ideal level, but they trade this self-image payoff against other material payoffs within their utility function (Brekke *et al.,* 2003). For heterogeneous agents, the Kantian hypothetical of all agents doing the same thing changes since different incomes, preferences and circumstances result in different optimum consumption levels. Therefore, Roemer (2010, 2015, 2019) suggests that a fully Kantian agent would contemplate all others deviating from their current action by the same proportion, optimising consumption at the point where no one would wish for everyone to deviate. A partially Kantian agent may calculate their moral utility through this method and trade it off against material utility or derive more nuanced self-image payoffs from consuming close to this morally ideal level (Long, 2021).

Given the negligible impact that an individual consumer has on the environment, consequentialist altruism and environmentalism fail to sufficiently motivate clean behaviours. Furthermore, since many clean behaviours are performed privately, thus are unobserved, social norms and reputation fail to comprehensively capture motivation. This suggests that there is some intrinsic, moral motivation behind green consumerism that is intricately linked to the positive contribution made to the environment and society.

Within this paper, we focus on how optimal taxes can be set on both clean and dirty goods when consumers optimise their consumption of dirty goods according to Roemer's (2010, 2015) conception of Kantian morality. Roemer's formalisation allows us to model agents with heterogeneous preferences and incomes, facilitating investigation into how different patterns of diversity influence optimal tax system design. To do this we employ and expand upon the Ramsey model of optimal second-best commodity taxation (Ramsey, 1927).

The Ramsey model of optimal commodity taxation (Ramsey, 1927; Myles, 1995, ch4) presents a general equilibrium model of taxation whereby the government must raise a given revenue requirement through second-best distortionary commodity taxes. In the baseline Ramsey model, identical consumers are modelled through a representative household. Optimal taxes raise the required revenue at the lowest cost to social welfare, maximising efficiency. This leads to the Ramsey Rule which states that the proportional change in compensated demands should be equal across all goods, implying that, when cross-price elasticities are minimal, goods with lower price elasticity of demand should bear the highest taxes.

Diamond and Mirrlees (1971), Diamond (1975) and Mirrlees (1975) extend the Ramsey model to consider the distributional effects of optimal taxes in the presence of heterogeneous households that have different social marginal utility of income. Optimal taxes raise the required revenue at the lowest cost to social welfare, optimising the trade-off of efficiency and equity. Efficiency considerations encourage higher taxes on price inelastic goods, whilst equity considerations encourage lower taxes on goods consumed disproportionately by households with higher social marginal utilities of income and hence lower incomes.

Sandmo (1975) and Sadka (1978) (see also Bovenberg and de Mooij, 1994; Bovenberg and van der Ploeg, 1994) extend the Ramsey model with heterogeneous households to include goods with externalities, whereby corrective Pigouvian taxation is introduced alongside optimal revenue-raising Ramsey taxation. Optimal taxes balance the competing goals of efficiency, equity, and environmental sustainability while raising the required revenue. Dirty goods are subject to revenue-raising Ramsey taxes and additional corrective Pigouvian environmental levies. When these levies conflict with efficiency or equity objectives, they are set below the first best Pigouvian corrective tax, only partially internalising environmental externalities.

This paper contributes to the literature by incorporating moral consumers into the Ramsey model to investigate how green consumerism affects optimal taxation. A further contribution is to investigate the case of heterogeneous preferences to highlight how the variance of preferences and the correlation between preferences and income influence patterns of optimal taxation.

The effect of green consumerism on optimal taxation has been studied within partial equilibrium models in a first-best setting. Within these models, the authors investigate the effects of green consumerism on the level of corrective Pigouvian taxation (Dasgupta *et al.,* 2016; Eichner and Pethig, 2022). These models tend to adopt homogeneous preferences, investigating how taxes vary with the degree of morality. Through employing the Ramsey optimal taxation framework, we will investigate the effects of green consumerism on the broader tax system in a second-best setting where the government has a revenue requirement and lump-sum taxes are infeasible. Furthermore, by adopting Roemer's (Roemer 2010) model of heterogeneous moral optimisation, we will explore how heterogeneous preferences and incomes influence patterns of optimal taxation within a perfectly moral population.

The remainder of this paper outlines and proves the theoretical model. We will first set up the consumer problem with moral preferences, whereby consumers optimise their consumption of a dirty good, a clean good, and leisure subject to a budget constraint. We will then set out the government's problem to raise a given revenue requirement at minimum cost to social welfare by charging taxes on dirty and clean goods, taking into account the behaviour of consumers. We will then investigate the Ramsey revenue-raising tax and the Pigouvian corrective tax in four key cases: (1) Non-moral homogeneous consumers, (2) Non-moral heterogeneous consumers, (3) Moral homogeneous consumers, and (4) Moral heterogeneous consumers. We will discuss the influence of morality and heterogeneity on the optimal levels of taxation. Finally, we will conclude by discussing the limitations of the model and highlighting areas for future exploration.

1.2 Model

1.2.1 Model Set Up

We consider an economy with H households, each seeking to optimise their utility subject to a budget constraint. Each household $h \in \{1, \dots, H\}$ derives utility from the consumption of a dirty good, z^h, a clean good, x^h, and leisure, $\left(1 - l^h\right)$, where total time is normalised to one and l^h represents the time allocated to labour. Additionally, each household experiences disutility from pollution externalities caused by the aggregate consumption of the dirty good, defined as $Z = \sum_{h=1}^{H} z^h$.

For simplicity, we assume the utility function of each household is additively separable and homothetic, represented as,

$$U^h = \ln\left(z^h\right) + \theta^h \ln\left(x^h\right) + \eta^h \ln\left(1 - l^h\right) - \phi(Z), \tag{1.1}$$

where $\theta^h > 0$ and $\eta^h > 0$ represent household h's preferences for the clean good and leisure, respectively, relative to the dirty good. The term $\phi(Z)$ is the damage function, capturing the disutility from pollution externalities. It is assumed to be differentiable, increasing, and convex with respect to Z.[1]

Additive separability implies that the marginal utility derived from each good (dirty good, clean good, and leisure) is independent of the household's consumption of other goods, simplifying the analysis of consumer behaviour. Homothetic preferences result in linear Engle curves (income offer curves) passing through the origin, meaning that as income scales up or down, the demanded bundle is scaled proportionally, preserving the ratio of goods consumed. Consequently, the ratio of demand for the clean good, the dirty good, and leisure is independent of household income.

The logarithmic functional forms for $z^h, x^h,$ and $(1 - l^h)$ preference indicate that utility is an increasing, concave function of these variables, implying diminishing marginal utility for consumption and leisure. The damage function $\phi(Z)$ captures the disutility from aggregate dirty good consumption. We assume that the population is large enough for each household's contribution to Z has a negligible individual impact.

These preferences have several desirable properties that simplify the model exposition and facilitate comparisons with the baseline Ramsey Rule. Firstly, when externalities are absent and consumers are homogeneous, the homothetic utility function implies that uniform taxation is optimal under neoclassical utility optimisation, thus the baseline Ramsey Rule can be recovered. Secondly, where consumers are homogeneous, households consume goods in the same proportions regardless of income, meaning that in such cases, the many-household Ramsey Rule reduces to the single-household version, and commodity taxes cannot serve a redistributive purpose. This focuses attention on the balance between efficiency and environmental sustainability objectives, putting equity to one side. Finally, homothetic utility functions allow for aggregation across households, enabling the calculation of aggregate demand elasticities, which simplifies the analysis of collective behaviour and policy impacts.

We assume that consumer goods are produced using constant returns to scale technology within competitive markets, such that profit-maximising firms generate zero real profits. Households and the government treat producer prices, $p_z, p_x,$ and wage rates, w^h, as fixed. Household-specific wage rates reflect household-specific labour productivities which are also assumed to be fixed. The market prices faced by consumers are a combination of the fixed producer price plus the optimal commodity taxation charged by the government. We assume that taxes on labour income are normalised to zero, such that individuals face a wage rate, w^h, and market prices, $q_z = p_z + t_z$ and $q_x = p_x + t_x$. Therefore,

[1] $\phi'(Z) > 0, \phi''(Z) > 0$

consumers who receive income from their labour, $w^h l^h$, and an additional lump-sum income, I^h, face a budget constraint of

$$q_z z^h + q_x x^h = w^h l^h + I^h. \tag{1.2}$$

We consider a government that must set commodity taxes, $t_z = q_z - p_z$ and $t_x = q_x - p_x$, to generate an exogenous revenue requirement, R, at minimum cost to social welfare. To simplify the model and to facilitate direct comparison with the baseline Ramsey model, we assume that there is no lump sum taxation and that the whole revenue requirement must be raised via optimal commodity taxes. The government must take into account how consumer demand responds to changes in the market price resulting from tax rate changes. The government is assumed to optimise a Bergson-Samuelson social welfare function, where social welfare, W, is a function of all households' indirect utility functions, $V^h(q_z, q_x, w^h, I^h)$,

$$W = W\big(V_1(q_z, q_x, w^1, I^1), \dots, V_H(q_z, q_x, w^H, I^H)\big), \tag{1.3}$$

subject to their revenue constraint,

$$(q_z - p_z)Z + (q_x - p_x)X = R. \tag{1.4}$$

1.2.2 The Moral Consumer Problem

To capture green consumerism, we model households to optimise their consumption of the dirty good according to Roemer's (2010, 2015) formalisation of Kant's categorical imperative. Ethical considerations are relevant in the case of dirty good consumption due to the negative environmental externalities which affect the utility of all households. Such considerations are irrelevant in the case of the clean good and leisure consumption since these are independent, individualistic choices which affect only the utility of the decision-makers. Thus, the optimal consumption of the moral consumer would coincide with that of the neoclassical consumer.

We employ Roemer's formalisation of Kant's categorical imperative.

"A strategy profile is a Kantian equilibrium if no player would like all players to alter their contributions by the same multiplicative factor."

Roemer (2010, p1)

Therefore, when choosing their consumption of the dirty good, households consider both themselves and all other agents to deviate from their current consumption by the same multiplicative factor, γ^h, such that their own consumption is represented as $\gamma^h z^h$, and aggregate consumption is $\gamma^h Z$. The Lagrangian can be set up as follows:

$$\mathcal{L}^h = \ln(\gamma^h z^h) + \theta^h \ln(x^h) + \eta^h \ln(1 - l^h) - \phi(\gamma^h Z) + \alpha^h\{I^h + w^h l^h - q_z \gamma^h z^h - q_x x^h\}\,, \quad (1.5)$$

where the Lagrange multiplier, α^h, represents the marginal utility of income. To optimise consumption of the dirty good, the moral consumer would choose the proportional deviation from current consumption levels which would maximise their own utility given their budget constraint. Therefore, the Lagrangian is differentiated with respect to the proportional deviation. The morally optimal level of z^h would be at the point where the agent would not wish for all agents to deviate from their current consumption levels by any common amount, i.e., $\gamma^h = 1$.

$$\left.\frac{\partial \mathcal{L}^h}{\partial \gamma^h}\right|_{\gamma^h=1} = 1 - \phi'(Z)Z - \alpha^h q_z z^h = 0\,. \quad (1.6)$$

Rearranging this gives the Kantian first-order condition for the dirty good,

$$z^h = \frac{1 - \phi'(Z)Z}{\alpha^h q_z}. \quad (1.7)$$

Consumption of the clean good and leisure will follow neoclassical consumer optimisation, whereby the Lagrangian is differentiated with respect to the quantity demanded of each good, and then set to zero. This gives the usual first-order conditions,

$$x^h = \frac{\theta^h}{\alpha^h q_x} \quad (1.8)$$

$$(1 - l^h) = \frac{\eta^h}{\alpha^h w^h} \quad (1.9)$$

From these three first-order conditions (Eq. 1.7-1.9) and the budget constraint (Eq. 1.2), we can obtain an expression for the marginal utility of income and the demand function for each good.

$$\alpha^h = \frac{(1 + \theta^h + \eta^h - \phi'(Z)Z)}{w^h + I^h}\,, \quad (1.10)$$

$$z^h = \frac{(1 - \phi'(Z)Z)\left(w^h + I^h\right)}{(1 + \theta^h + \eta^h - \phi'(Z)Z)q_z}, \tag{1.11}$$

$$x^h = \frac{\theta^h\left(w^h + I^h\right)}{(1 + \theta^h + \eta^h - \phi'(Z)Z)q_x}, \tag{1.12}$$

$$\left(1 - l^h\right) = \frac{\eta^h\left(w^h + I^h\right)}{(1 + \theta^h + \eta^h - \phi'(Z)Z)w^h} . \tag{1.13}$$

We assume that the product of the aggregate consumption of the dirty good and marginal damage from aggregate consumption is less than one, $\phi'(Z)Z < 1$,[2] such that each household will have strictly positive demands for both goods and leisure. Additionally, we assume that lump sum income is low enough that it will always be optimal to work even at the lowest wage rates. This avoids a corner solution in equation 1.13, ensuring that leisure time is less than the individual's time endowment.

Equations 1.10 to 1.13 demonstrate that the consumption patterns of Kantian moral consumers are influenced by the consumption of all other consumers. In the Kantian optimisation process, households consider the effect of all consumers deviating by the same proportion, thus changes to the externality are significant and will influence their demand function through the term, $0 < \phi'(Z)Z < 1$. This contrasts with the consumption patterns of non-Kantian consumers. In the neoclassical optimisation process, households assume aggregate consumption of the dirty good is given and their own contribution to it is negligible. Therefore, in the neoclassical case, demands differ from the moral case in equations 1.11-1.13, in that each of the terms $-\phi'(Z)Z = 0$ (i.e., in the numerator of equations 1.10 and 1.11, and the denominator of equations 1.11, 1.12 and 1.13).

First, since $\phi'(Z)Z > 0$ for moral consumers, we can see that consumption of the dirty good (Eq. 1.11) will be lower for the Kantian consumer, since $\phi'(Z)Z$ reduces the numerator to a greater extent than it reduces the denominator. This demonstrates that moral consumers internalise some of the environmental externality by reducing their own consumption of the dirty good. Secondly, we can see that for both the clean good (Eq. 1.12) and leisure (Eq. 1.13), the externality reduces the value of the denominator only, resulting in higher consumption. The rationale for an increase in consumption of the clean good is that a reduction in consumption of the dirty good frees up income to spend on the clean good. The rationale for an increase in leisure is that a decrease in consumption of the dirty good decreases demand for income, hence the individual may work less and enjoy more leisure time.

[2] This can be obtained from the first order condition for moral dirty good consumption in equation 1.7, since $q_z > 0$ and $\alpha^h > 0$. If $\phi'(Z)Z > 1$ then all Kantians would want to reduce their consumption, lowering Z. Thus, $\phi'(Z)Z < 1$ is the only stable equilibrium of the moral consumer problem.

We can also see how individuals' preferences and incomes influence their demands. For example, a higher preference for the clean good relative to the dirty good, θ^h, will increase demand for the clean good whilst reducing demands for both the dirty good and leisure. Higher lump-sum income, I^h, will increase demand for both consumption goods and for leisure, meanwhile, higher wage income, w^h, will increase demand for consumption goods, but will reduce demand for leisure.[3] This demonstrates how moral consumers continue to trade off the benefit of higher individual consumption of the dirty good against the cost of higher aggregate consumption, with consumers with dirtier preferences or higher incomes consuming more dirty goods.

Subsequently, the indirect utility or the value function of the consumer can be derived by substituting these demands back into the consumer utility function.

$$V^h = ln\left(\frac{(1-\phi'(Z)Z)(w^h+I^h)}{(1+\theta^h+\eta^h-\phi'(Z)Z)q_z}\right)+\theta^h\, ln\left(\frac{\theta^h(w^h+I^h)}{(1+\theta^h+\eta^h-\phi'(Z)Z)q_x}\right)$$
$$+\eta^h\, ln\left(\frac{\eta^h(w^h+I^h)}{(1+\theta^h+\eta^h-\phi'(Z)Z)w^h}\right)-\phi(Z). \tag{1.14}$$

From the indirect utility, the consumer’s response to changes in the market price of the dirty good and the clean good can be calculated.

$$\frac{\partial V^h}{\partial q_z} = -\frac{1}{q_z}-\left[1+\frac{(\theta^h+\eta^h)(\phi''(Z)Z+\phi'(Z))Z}{(1-\phi'(Z)Z)(1+\theta^h+\eta^h-\phi'(Z)Z)}\right]\phi'(Z)\frac{\partial Z}{\partial q_z}$$
$$= -\frac{1}{q_z}-\phi'(Z)(1+m^h)\frac{\partial Z}{\partial q_z}, \tag{1.15}$$

where

$$m^h = \frac{(\theta^h+\eta^h)(\phi''(Z)Z+\phi'(Z))Z}{(1-\phi'(Z)Z)(1+\theta^h+\eta^h-\phi'(Z)Z)} > 0 \tag{1.16}$$

captures the influence of moral preferences.[4]

Meanwhile,

$$\frac{\partial V^h}{\partial q_x} = -\frac{\theta^h}{q_x}. \tag{1.17}$$

[3] When we have log utility and positive lump sum income, the substitution effect will dominate the income effect. Higher wages make leisure more expensive causing agent to substitute towards labour.

[4] A non-moral consumer would have partial derivative: $\frac{\partial V^h}{\partial q_z} = -\frac{1}{q_z}-\phi'(Z)\frac{\partial Z}{\partial q_z}$

Equation 1.17 demonstrates that a change in the price of the clean good only influences indirect utility via their demand for the clean good. This is due to the aggregate demand for the dirty good being independent of the price of the clean good, as can be seen from the aggregation and partial differentiation of household demand for the dirty good in equation 1.11.

Whereas equation 1.15 demonstrates that an increase in the market price of the dirty good has two effects. The first term on the right-hand side in equation 1.15 demonstrates a reduction in utility due to private consumption becoming more expensive. Meanwhile, the second term demonstrates an increase in utility due to lower aggregate consumption reducing external damages.

In equation 1.15, m^h represents the influence of morality. We can deduce that for Kantian moral consumers $m^h > 0$,[5] whilst for non-Kantian consumers $m^h = 0$. This suggests that a change in the price of the dirty good will have a larger positive component for Kantian moral consumers, implying that they will suffer less from an increase in dirty good taxes and thereby their demand will be less responsive to changes in the tax rate. This is because moral consumers have already voluntarily reduced their consumption of the dirty good by taking into account aggregate externalities, therefore when there is a price increase which reduces all households' individual consumption of the dirty good and subsequently reduces aggregate consumption and aggregate externalities, the moral consumer will have a smaller externality to seek to internalise. The negative term in the denominator of the dirty good demand would reduce, thus there will be a positive force upon individual dirty good demands, overall resulting in a smaller reduction in dirty good demand in response to a price change.

1.2.3 The Government Problem

Given the behaviour of households, the government aims to choose tax rates to maximise social welfare (Eq. 1.3) subject to its revenue constraint (Eq. 1.4). The government's optimisation problem may be represented through the Lagrangian,

$$\mathcal{L} = W\big(V_1(.), V_2(.), \dots, V_H(.)\big) + \lambda\{(q_z - p_z)Z + (q_x - p_x)X - R\}, \tag{1.18}$$

[5] From equation 1.12, if $x^h > 0$ then $(1 + \theta + \eta - \phi'(Z)Z) > 0$. From equation 1.11, if $z^h > 0$, since we have established the denominator is positive, $(1 - \phi'(Z)Z) > 0$. Finally, since the pollution damage function is increasing and convex, we know that $\big(\phi''(Z)Z + \phi'(Z)\big) > 0$. Consequently, $m = \frac{(\theta+\eta)\big(\phi''(Z)Z+\phi'(Z)\big)Z}{(1-\phi'(Z)Z)(1+\theta+\eta-\phi'(Z)Z)} > 0$.

where $V_h(.), h = 1, \dots, H$ represents the indirect utility function for each household as set out in equation 1.14, λ is the Lagrange multiplier, and the government chooses tax rates $t_z = q_z - p_z$ and $t_x = q_x - p_x$. Here, the aggregate consumption of the dirty and the clean goods, Z and X respectively, are consistent with the aggregation of household demand functions in equations 1.11 and 1.12.

The first order condition for the choice of the tax on the dirty good is

$$\frac{\partial \mathcal{L}}{\partial q_z} = \sum_{h=1}^{H} \frac{\partial W}{\partial V^h}\left(-\frac{1}{q_z} - \phi'(Z)\left(1 + m^h\right)\frac{\partial Z}{\partial q_z}\right) + \lambda\left(Z + (q_z - p_z)\frac{\partial Z}{\partial q_z} + (q_x - p_x)\frac{\partial X}{\partial q_z}\right) = 0\,. \quad (1.19)$$

As shown in Appendix A2, the dual cost minimisation problem is consistent with the consumer's utility optimisation for moral consumers, henceforth Slutsky substitution can be used to decompose the terms in the second large bracket into a substitution effect and an income effect.

$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial q_z} = &\sum_{h=1}^{H} \frac{\partial W}{\partial V^h}\left(-\frac{1}{q_z} - \phi'(Z)\left(1 + m^h\right)\frac{\partial Z}{\partial q_z}\right)\\ &+\lambda\left(Z + (q_z - p_z)\frac{\partial Z^c}{\partial q_z} + (q_x - p_x)\frac{\partial X^c}{\partial q_z} - \left(t_z\frac{\partial Z}{\partial \bar{I}} + t_x\frac{\partial X}{\partial \bar{I}}\right)Z\right) = 0 \qquad (1.20)\end{aligned}$$

As shown in Appendix A3, the symmetry of the Slutsky substitution terms also holds within the Kantian model, therefore $\frac{\partial X^c}{\partial q_z} = \frac{\partial Z^c}{\partial q_x}$.

$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial q_z} = &\sum_{h=1}^{H} \frac{\partial W}{\partial V^h}\left(-\frac{1}{q_z} - \phi'(Z)\left(1 + m^h\right)\frac{\partial Z}{\partial q_z}\right)\\ &+\lambda\left(Z + (q_z - p_z)\frac{\partial Z^c}{\partial q_z} + (q_x - p_x)\frac{\partial Z^c}{\partial q_x} - \left(t_z\frac{\partial Z}{\partial \bar{I}} + t_x\frac{\partial X}{\partial \bar{I}}\right)Z\right) = 0 \qquad (1.21)\end{aligned}$$

Following this, the middle two terms in the second bracket can be transformed through a first-order Taylor approximation.[6] Subsequently, equation 1.21 can be rearranged to give a formula for the percentage change in compensated demand for the dirty good under the optimal taxation system,

[6] $Z^c(q_z, q_x, u) \approx Z^c(p_z, p_x, u) + (q_z - p_z)\frac{\partial Z^c(p_z,p_x,u)}{\partial q_z} + (q_x - p_x)\frac{\partial Z^c(p_z,p_x,u)}{\partial q_x}$. Therefore, $\Delta Z^c \approx (q_z - p_z)\frac{\partial Z^c}{\partial q_z} + (q_x - p_x)\frac{\partial Z^c}{\partial q_x}$.

$$\frac{\Delta Z^c}{Z} = \frac{1}{\lambda}\sum_{h=1}^{H}\frac{\partial W}{\partial V^h}\left(\frac{1}{q_z} + \phi'(Z)\left(1+m^h\right)\frac{\partial Z}{\partial q_z}\right)\frac{1}{Z} - 1 + t_z\frac{\partial Z}{\partial \bar{I}} + t_x\frac{\partial X}{\partial \bar{I}}\ . \tag{1.22}$$

Similarly, for the change in compensated demand for the clean good, we obtain,

$$\frac{\Delta X^c}{X} = \frac{1}{\lambda}\sum_{h}^{H}\frac{\partial W}{\partial V^h}\frac{\theta^h}{q_x}\frac{1}{X} - 1 + t_z\frac{\partial Z}{\partial \bar{I}} + t_x\frac{\partial X}{\partial \bar{I}}. \tag{1.23}$$

It should be noted that equations 1.22 and 1.23 for the proportional change in compensated demand are approximations that become arbitrarily accurate as the tax rates get arbitrarily small, i.e., as the revenue requirement, R, becomes arbitrarily small.

1.2.4 The Ramsey Rule

If the Ramsey Rule holds, then, in a system of optimal second-best commodity taxation, the percentage change in compensated demand is the same for all goods, i.e., $\frac{\Delta Z^c}{Z} = \frac{\Delta X^c}{X}$. The economics literature demonstrates that when consumers are heterogeneous or when there are consumption externalities, the efficiency objective of the Ramsey Rule must balance with equity and environmental objectives (Diamond and Mirrlees, 1971; Diamond, 1975; Mirrlees, 1975; Sandmo, 1975; Sadka, 1978). We analyse the equivalence of equations 1.21 and 1.22 to investigate how the deviations from the Ramsey Rule are influenced by morality, both in the case of homogeneous and heterogeneous households.

We carry out this investigation for four key cases, (1) Non-moral agents with homogeneous preferences, (2) Non-moral agents with heterogeneous preferences, (3) Moral agents with homogeneous preferences, and (4) Moral agents with heterogeneous preferences, as shown in table 1.1. We highlight how both morality and heterogeneity influence optimal taxes.

Table 1.1: Four versions of the model and their chapter sections

	Homogeneous	Heterogeneous
Non-Moral	Section 1.2.4.1	Section 1.2.4.2
Moral	Section 1.2.4.3	Section 1.2.4.4

For simplicity of exposition, we assume that the government has a utilitarian social welfare function, such that social welfare is the unweighted sum of individual utilities, $W = V_1(.) + \cdots + V_H(.)$, and $\frac{\partial W}{\partial V^h} = 1 \ \forall h$. Consequently, within this utilitarian framework, we evaluate,

$$\frac{\Delta Z^c}{Z} - \frac{\Delta X^c}{X} = \frac{1}{\lambda}\left(\sum_{h=1}^{H}\left(\frac{1}{q_z} + \phi'(Z)\left(1 + m^h\right)\frac{\partial Z}{\partial q_z}\right)\frac{1}{Z} - \sum_{h}^{H}\frac{\theta^h}{q_x X}\right). \quad (1.24)$$

<u>*1.2.4.1 Non-Moral Consumers with Homogeneous Preferences*</u>

> ***Proposition 1:*** *When consumers have homogeneous preferences and optimise in a neoclassical manner an additional corrective Pigouvian tax must be levied on the dirty good to internalise negative environmental externalities. Optimal Ramsey taxes are uniform.*

When consumers optimise in a non-moral, neoclassical way, they assume external effects are constant. This is because they hold constant the consumption of other agents whilst assuming their own consumption has negligible effects on aggregate consumption level. Therefore, the term representing the marginal damage of negative externalities, $\phi'(Z)Z$, will disappear from the demand functions (Eq. 1.11 to 1.13), and subsequently, the morality term, m^h, disappear in the consumer's utility response to price changes (Eq. 1.15, 1.22, 1.24).

To evaluate equation 1.24, we must express the different parts of the equation in the same terms. First, we can substitute the non-moral expression for the partial differential, $\frac{\partial Z}{\partial q_z} = -\frac{Z}{q_z}$. Second, we can substitute the expression for the aggregate clean good demand in terms of the dirty good demand, $\frac{1}{X} = \frac{q_x}{q_z}\frac{1}{\sum_{h=1}^{H}\theta^h z^h}$. We can then rearrange the equation to investigate the Ramsey Rule in the case of non-moral agents, setting $m^h = 0$.

$$\frac{\Delta Z^c}{Z} - \frac{\Delta X^c}{X} = \frac{1}{\lambda}\frac{1}{q_z}\left(\sum_{h=1}^{H}\left(\frac{1}{Z} - \phi'(Z)\right) - \sum_{h}^{H}\left(\frac{\theta^h}{\sum_{h=1}^{H}\theta^h z^h}\right)\right) \quad (1.25)$$

When households have homogeneous preferences, $\theta^h = \theta, \eta^h = \eta, \forall h$. For homogeneous agents, equation 1.25 simplifies to,

$$\frac{\Delta Z^c}{Z} - \frac{\Delta X^c}{X} = -\frac{H}{\lambda}\frac{\phi'(Z)}{q_z}. \tag{1.26}$$

Therefore, when we have non-moral consumers with homogeneous preferences, the Ramsey rule does not hold, the optimal tax system causes a larger compensated proportional reduction in dirty good consumption equal to the value of the marginal damages. Thus, an additional Pigouvian corrective tax[7] equal to this value must be charged. This matches the findings of Sandmo (1975) and Bovenberg and de Mooij (1994) who introduce dirty goods into the Ramsey optimal taxation model with neoclassical consumer preferences.

We can further investigate the nature of revenue-raising Ramsey taxes within this context by calculating the price elasticity of demand for the dirty good and the clean good. In Appendix A1, we find that $\varepsilon_Z = \frac{\partial Z}{\partial q_z}\frac{q_z}{Z} = \varepsilon_X = \frac{\partial X}{\partial q_x}\frac{q_x}{X} = -1$. This implies that the revenue-raising component of the tax rates will be uniform across the dirty good and the clean good because the demand for both goods is equally responsive the changes in the price.

If there were no externalities, such that $\phi(Z) = \phi'(Z) = 0$, then the model reduces to the baseline representative household Ramsey model, whereby in the system of optimal taxation the Ramsey Rule of equi-proportionate reduction in compensated demands holds.

1.2.4.2 Non-Moral Consumers with Heterogeneous Preferences

When consumers optimise in a non-moral, neoclassical way but have heterogeneous preferences, the discrepancy between the optimal proportional change in demand for the dirty good and the optimal proportional change in demand for the clean good will depend upon the distribution of preferences and the correlation between preferences and income.

> ***Proposition 2:*** *When consumers optimise in a neoclassical manner and have heterogeneous preferences for the clean good and homogeneous income, the additional corrective Pigouvian tax levied on the dirty good to internalise negative environmental externalities is exacerbated by preference heterogeneity. Optimal Ramsey taxes are uniform.*

[7] We define the discrepancy between $\frac{\Delta Z^c}{Z}$ and $\frac{\Delta X^c}{X}$ to the 'Pigouvian tax' since in the scenario where $R = 0$ and there is no Ramsey tax, a corrective Pigouvian tax would still be required to achieve the social optimum.

Proposition 2 assumes that preference for leisure and household income are homogeneous.[8] When agents have heterogeneous preferences for the clean good, the first term within $\frac{\Delta Z^c}{Z}$ no longer cancels with $\frac{\Delta X^c}{X}$ in equation 1.25. The contribution of these terms, $\frac{1}{\lambda}\frac{1}{q_z}\left(\frac{H}{Z}-\sum_{h=1}^{H}\frac{\theta^h}{\sum_{h=1}^{H}\theta^h z^h}\right)$, depends upon the relation between clean good preference and dirty good demand. When income is homogeneous, it is clear to see that there is a negative relation between preference for the clean good, θ^h, and demand for the dirty good, z^h. This is clear from the partial differential of the dirty good demand function with respect to the clean good preference, $\frac{\partial z^h}{\partial \theta^h} = -\frac{w^h+I^h}{\left(1+\theta^h+\eta^h\right)^2 q_z} < 0$. Henceforth, in the population, there will be a negative covariance between the two, $\text{Cov}\left(\theta^h, z^h\right) < 0$. The formula for covariance demonstrates that the first two terms inside the bracket in equation 1.25 will have a negative contribution. $\text{Cov}\left(\theta^h, z^h\right) = \frac{1}{H-1}\left(\sum_{h=1}^{H}\theta^h z^h - \frac{1}{H}\sum_{h=1}^{H}\theta^h \sum_{h=1}^{H} z^h\right) < 0$, rearranges to show that

$$\frac{H}{Z} - \frac{\sum_{h=1}^{H}\theta^h}{\sum_{h=1}^{H}\theta^h z^h} < 0.$$

Henceforth, when income is independent of preferences, preference heterogeneity increases the size of the negative environmental externality, resulting in a higher corrective Pigouvian tax under the optimal tax system. As the variance of clean good preferences increases, this effect intensifies.

> ***Proposition 3:*** *When consumers optimise in a neoclassical manner and have heterogeneous preferences for the clean good,*
>
> ***(a)*** *When income is negatively correlated with clean good preference, the exacerbation of the additional Pigouvian tax by preference heterogeneity is increased.*
>
> ***(b)*** *When income is positively correlated with clean good preference, the exacerbation of the additional Pigouvian tax by preference heterogeneity is reduced.*

Proposition 3 assumes that preference for leisure is homogeneous across households. If income is also heterogeneous and clean good preferences vary systematically with income, the overall effect on optimal taxation will depend upon the sign and strength of the correlation between preferences and income.

The first two terms in equation 1.25 still depend upon the relation between clean good preference and dirty good demand, however, this relation will now be influenced by income. To investigate this influence, we can expand the covariance function,

---

[8] Thus, $\text{Cov}(w^h + I^h, \theta^h) = 0$, $\text{Cov}(w^h + I^h, \eta^h) = 0$, $Cov(\theta^h, \eta^h) = 0$.

$$\begin{aligned}\text{Cov}(\theta^h, z^h) &= \text{Cov}\left(\theta^h, \frac{(I^h + w)}{(1 + \theta^h + \eta)q_z}\right) \\ &= \frac{1}{(H-1)q_z}\left[\sum_{h=1}^{H} \frac{(\theta^h - \bar{\theta})(I^h + w)}{1 + \theta^h + \eta^h}\right]. \end{aligned} \tag{1.27}$$

For simplicity, we have assumed wage income and preference for leisure to be homogeneous. If income were also homogeneous, we would have $\frac{1}{(H-1)q_z}\left[\sum_{h=1}^{H} \frac{(\theta^h - \bar{\theta})}{1+\theta^h+\eta}\right] < 0$ as above.

If income is negatively correlated with clean good preference, this implies that richer people have dirtier preferences, and therefore, when clean good preference is below average, $(\theta^h - \bar{\theta}) < 0$, it will be multiplied by a larger income within the summation, $(I^h + w)$. Henceforth, when summed across all households, the overall covariance between clean good preference and dirty good consumption will become *more* negative. This occurs because households with higher incomes will overconsume the dirty good to a much greater extent, exacerbating the covariance between clean good preference and dirty good demand. Overall, this increases the residual externality due to overconsumption by the rich not being compensated for by constrained consumption of lower income, cleaner households, and therefore the optimal Pigouvian taxation increases.

On the other hand, if income is positively correlated with clean preference, this implies that richer people have cleaner preferences, and now when clean good preference is above average, $(\theta^h - \bar{\theta}) > 0$, it will be multiplied by a larger income within the summation of equation 1.27. Henceforth, when summed across all households there will be a larger positive component, reducing the negative covariance between clean good preference and dirty good demand. This occurs because households with higher income will spend more on all commodities, both clean and dirty goods, henceforth despite having a lower preference for dirty goods they may still consume a considerable amount. Additionally, those with dirtier preferences do not have as much income to overconsume dirty goods. Overall, this reduces the covariance between clean good preference and dirty good demand, reducing the residual externality and the corresponding optimal Pigouvian tax.

Within the context of heterogeneous preferences, we find that the price elasticities of demand for the dirty good and the clean good are still identical and equal to -1. Therefore, optimal Ramsey revenue-raising taxes will still be uniform.

1.2.4.3 Moral Consumers with Homogeneous Preferences

> ***Proposition 4:*** *When consumers have homogeneous preferences and optimise in a Kantian moral manner, the Ramsey rule holds, hence no additional corrective Pigouvian tax must be levied on the dirty good. Optimal Ramsey taxes will be relatively higher on the dirty good due to moral optimisation resulting in a relatively lower price elasticity of demand.*

To evaluate equation 1.24 in the presence of moral consumers we must repeat the exercise at the beginning of subsection 1.2.4.1, to express the equations in the same terms, now using expressions from moral optimisation. First, we can substitute the moral expression for the partial derivative, $\frac{\partial Z}{\partial q_z} = -\frac{Z}{q_z}\frac{1}{\left(1+\frac{\sum_{h=1}^{H} m^h z^h}{Z}\right)}$ from equation A1.4 in Appendix A. Second, we can substitute the expression for aggregate clean good in terms of the dirty good, $\frac{1}{X} = \frac{(1-\phi'(Z)Z)q_x}{q_z}\frac{1}{\sum_{h=1}^{H} z^h\theta^h}$. We can then rearrange the equation to investigate the Ramsey rule in the case of moral agents.

$$\frac{\Delta Z^c}{Z} - \frac{\Delta X^c}{X} = \frac{1}{\lambda}\frac{1}{q_z}\left(\sum_{h=1}^{H}\left(1-\phi'(Z)Z\frac{\left(1+m^h\right)}{1+\frac{\sum_{h=1}^{H} m^h z^h}{Z}}\right)\frac{1}{Z} - \sum_{h=1}^{H}\left((1-\phi'(Z)Z)\frac{\theta^h}{\sum\theta^h z^h}\right)\right) \quad (1.28)$$

When Kantian moral consumers have homogeneous preferences, $\theta^h = \theta, \eta^h = \eta$, and $m^h = m, \forall h$. For homogeneous agents, equation 1.28 simplifies to,

$$\frac{\Delta Z^c}{Z} - \frac{\Delta X^c}{X} = \frac{1}{\lambda}\frac{1}{q_z}\left(\sum_{h=1}^{H}\left(1-\phi'(Z)Z\frac{1+m}{1+m}\right)\frac{1}{Z} - \sum_{h=1}^{H}\left((1-\phi'(Z)Z)\frac{\theta}{\theta Z}\right)\right) = 0 \quad (1.29)$$

Therefore, when we have moral consumers with homogeneous preferences, the Ramsey rule holds. This implies that only Ramsey revenue-raising taxes are charged on all goods, there is no additional corrective Pigouvian tax charged on the dirty goods. This is because when all consumers are perfectly Kantian with homogenous preferences, they will each voluntarily internalise the externalities arising from their own consumption of the dirty good by reducing their consumption to the optimal level. This finding is consistent with Roemer (2010, 2015) who shows that in the context of voluntary contributions to a public good, all external effects are perfectly internalised in the Kantian equilibrium.

We can further investigate the nature of revenue-raising Ramsey taxes within this homogeneous moral environment. In Appendix A1, we find that the price elasticity of demand for the dirty good, $\varepsilon_Z = -\frac{1}{1+m}$, is less elastic than for the clean good, $\varepsilon_X = -1$, henceforth moral consumers' demand for the dirty good will be less responsive to changes in the price of the dirty good. Consequently, it is optimal to charge relatively higher Ramsey taxes on the dirty good, since demands will be distorted less, and the revenue requirement can be raised with lower costs to social welfare. This finding aligns with our intuition that the motivation of moral consumers is non-pecuniary.

1.2.4.4. Moral Consumers with Heterogeneous Preferences

When Kantian moral consumers have heterogeneous preferences, the Ramsey rule no longer holds. The residual externality and the optimal level of Pigouvian corrective tax will depend upon the distribution of preference and the correlation between preference and income.

> ***Proposition 5:*** *When consumers optimise in a Kantian moral manner and have heterogeneous clean good preferences, the Ramsey rule no longer holds.*
>
> *When income is homogonous, an additional corrective Pigouvian tax levied on the dirty good to internalise negative environmental externalities arising from preference heterogeneity. Optimal Ramsey taxes will be relatively higher on the dirty good due to moral optimisation resulting in a relatively lower price elasticity of demand.*

Proposition 5 assumes that preference for leisure and household income are homogeneous. When moral agents have heterogeneous preferences, as in section 1.2.4.2, the terms in in equation 1.28 no longer cancel out. Equation 1.28 can be simplified and re-arranged to investigate how heterogeneous preferences influence residual externalities.

$$\frac{\Delta Z^c}{Z} - \frac{\Delta X^c}{X} = \frac{1}{\lambda q_z Z}\left(\left(H - \frac{\sum_{h=1}^{H}\theta^h \sum_{h=1}^{H} z^h}{\sum_{h=1}^{H}\theta^h z^h}\right) - \phi'(Z)Z\left(\frac{HZ + \sum_{h=1}^{H} m^h \sum_{h=1}^{H} z^h}{Z + \sum_{h=1}^{H} m^h z^h} - \frac{\sum_{h=1}^{H}\theta^h \sum_{h=1}^{H} z^h}{\sum_{h=1}^{H}\theta^h z^h}\right)\right) \quad (1.30)$$

The contribution the term in the first bracket in equation 1.30 depends on the relation between clean good preferences and dirty good demand. The contribution of the term in the second bracket also depends on the relation between the morality term and dirty good demand.

When income is homogeneous or independent of preferences, it is clear to see that there is a negative relation between preference for the clean good, θ^h, and moral consumers demand for the dirty good,

z^h. This is clear from the partial differential, $\frac{\partial z^h}{\partial \theta^h} = -\frac{(1-\phi'(Z)Z)(I^h+w^h)}{(1+\theta^h+\eta^h-\phi'(Z)Z)^2 q_z} < 0$. Henceforth, as in section 1.2.4.2, $\frac{H}{Z} - \frac{\sum_{h=1}^{H}\theta^h}{\sum_{h=1}^{H}\theta^h z^h} < 0$, and thus $H - \frac{\sum_{h=1}^{H}\theta^h \sum_{h=1}^{H} z^h}{\sum_{h=1}^{H}\theta^h z^h} < 0$ the first bracket in equation 1.30 is negative.

Additionally, when income in homogeneous or independent of preferences, it is clear to see that there will be a positive relation between preference for the clean good and the morality term, $m^h = \frac{(\theta^h+\eta^h)(\phi''(Z)Z+\phi'(Z))Z}{(1+\theta^h+\eta^h-\phi'(Z)Z)(1-\phi'(Z)Z)}$. Again, this is clear from the partial differential, $\frac{\partial m^h}{\partial \theta^h} = \frac{(\phi''(Z)Z+\phi'(Z))Z}{(1+\theta^h+\eta^h-\phi'(Z)Z)^2} > 0$. Together, these two relations imply that a higher clean good preference is associated with both a smaller dirty good demand and a higher morality term, implying a negative relation between dirty good demand and the morality term, $\text{Cov}(z^h, m^h) < 0$. Expanding out the covariance, $\text{Cov}(z^h, m^h) = \frac{1}{H-1}\left(\sum_{h=1}^{H} z^h m^h - \frac{1}{H}\sum_{h=1}^{H} z^h \sum_{h=1}^{H} m^h\right) < 0$, rearranging and substituting this into the first term inside the second bracket of equation 1.30 gives, $\frac{HZ+\sum_{h=1}^{H} m^h \sum_{h=1}^{H} z^h}{Z+\sum_{h=1}^{H} m^h z^h} > H$. Together with the finding above that $\frac{\sum_{h=1}^{H}\theta^h \sum_{h=1}^{H} z^h}{\sum_{h=1}^{H}\theta^h z^h} > H$, this implies that the sign of the second bracket depends on the scale of the covariance between the two terms. We expect that the covariance between clean preference and demand will be stronger than the covariance between the morality term and demand, therefore, the second bracket will have a positive contribution which is smaller than the first bracket and further scaled down by $\phi'(Z)Z < 1$. Henceforth, when there are heterogeneous moral consumers, we expect that a residual externality arises from this heterogeneity, as we found in the case of non-moral agents in section 1.2.4.2.

If income is also heterogeneous and preferences vary systematically with income, the overall effect on optimal taxation will depend upon the sign and strength of the correlation between preferences and income.

> ***Proposition 6:*** *When consumers optimise in a Kantian moral manner and have heterogeneous clean good preferences, the Ramsey rule no longer holds.*
>
> ***(a)*** *When income is negatively correlated with clean good preference, the additional corrective Pigouvian tax charged on the dirty good to correct for residual externalities arising from preference heterogeneity will increase.*
>
> ***(b)*** *When income is positively correlated with clean good preference, the additional corrective Pigouvian tax charged on the dirty good to correct for residual externalities arising from preference heterogeneity will be reduced.*

Proposition 6 assumes that preference for leisure is homogenous across households. As in section 1.2.4.2, the relation between clean good preference and dirty good demand is influenced by the relation between clean good preference and income. When income is negatively correlated with clean good preference, such that richer consumers have dirtier preferences, both $\mathrm{Cov}(\theta^h, z^h)$ and $\mathrm{Cov}(z^h, m^h)$ will become more negative. Consequently, the first bracket in 1.30 will have a more negative contribution. Meanwhile, since the covariance between clean good demand and the morality term is likely to reduce to a larger extent, the second bracket is likely to become less positive and may even become negative if the correlation between income and preferences is strongly negative. Overall, the residual externality will be larger, requiring a higher optimal Pigouvian corrective tax.

On the other hand, if there is a positive correlation between income and clean goods preference, such that richer consumers have cleaner preferences, we observe the opposite. With both $\mathrm{Cov}(\theta^h, z^h)$ and $\mathrm{Cov}(z^h, m^h)$ becoming less negative, thus the first bracket will become less negative, whilst the second bracket will become more positive. Overall, there will be a smaller residual externality and a smaller optimal Pigouvian corrective tax.

1.3 Key Findings

We have developed a model to investigate optimal commodity taxation in the presence of both a dirty good with environmental externalities and a clean good. We have explored the influence of moral versus non-moral optimisation, and of homogeneous versus heterogeneous preferences.

Our first finding, in Proposition 1, is that, in the presence of homogeneous neoclassical consumers who maximise their material utility, an additional corrective tax is required to internalise externalities arising from dirty good consumption. This confirms the findings of Sandmo (1975), Sadka (1978), Bovenberg and de Mooij (1994) and Bovenberg and van der Ploeg (1994), that both a revenue-raising Ramsey tax and a corrective Pigouvian tax must be levied on dirty goods in a system of optimal taxation. The value of this tax corresponds to the marginal social cost of the externality.

Our second finding, in Propositions 2 and 3, is that the corrective Pigouvian element of the tax will increase when neoclassical consumers have heterogeneous preferences. This occurs due to the diminishing marginal utility of consumption. This causes overconsumption by agents with a stronger preference for the dirty good which is not compensated for by sufficient underconsumption by agents with a weaker preference for the dirty good.

This increase in optimal Pigouvian taxation is exacerbated when income is negatively correlated with clean good preference. In this case, richer individuals have dirtier preferences and thus have more income to spend on overconsuming the dirty good. Meanwhile, those with cleaner preferences cannot compensate for this higher level of overconsumption.

Our third finding, in Proposition 4, is that in the presence of homogeneous Kantian moral consumers who seek to 'do the right thing', all negative environmental externalities from dirty good consumption are internalised. This removes the need for external corrective interventions and means that the Ramsey Rule will hold. This aligns with Roemer's (2010, 2015) key result that Kantian optimisation solves collective action problems and perfectly internalises externalities.

Our fourth finding, in Propositions 5 and 6, is that when Kantian moral consumers have heterogeneous preferences, they are not able to fully internalise environmental externalities arising from dirty good consumption. This matches the finding in propositions 2 and 3 where externalities increase due to preference heterogeneity. In the case of moral consumers, this results in a residual externality which requires a Pigouvian-style tax to internalise. The value of this residual externality is determined by the negative correlation between dirty good consumption and clean good preference and also the negative correlation between dirty good consumption and the morality term. As above, we find this effect is exacerbated when income is negatively correlated with clean good preference and reduced in the case of positive correlation. Propositions 5 and 6 highlight the importance of adopting Roemer's (2010) formalisation of heterogeneous moral agents rather than a simpler model of a representative agent. They demonstrate how even fully moral agents fall short of achieving the social optimum, and that the residual externality will be determined by the direction and the size of the correlation between preferences, demand, and income.

Our fifth and final finding concerns the level of Ramsey revenue-raising tax levied on dirty goods relative to clean goods. When cross-price elasticities of demand are minimal, the Ramsey Rule implies that higher taxes should be levied on price inelastic goods since a higher revenue can be raised with less distortion to market demand and therefore less cost to social welfare. When agents optimise in a non-moral, neoclassical manner the Ramsey revenue-raising component of the tax will be uniform across consumption goods due to the uniform, unitary price elasticity of demand. When agents optimise in a Kantian moral manner a relatively higher Ramsey revenue-raising tax should be charged on the dirty good due to relatively more price inelastic demand. This emerges because moral consumers are motivated by their partiality to do the right thing, and thus will be less responsive to changes in the market price. The moral consumers' demand is a function of the external damages, subsequently, the morality term, m^h, captures how moral consumers' demand changes in response to a change in external damages which arise from a price change. For moral consumers, when the price of the dirty good increases, there is a direct effect of a higher price reducing demand, meanwhile there is a smaller, indirect effect of a higher price inducing lower external damages and subsequently increasing demand.

When the government increases the tax on the dirty good, some of the moral responsibility on the consumer is crowded out, and there is less pressure to reduce their consumption. This is also the case in Diamond (1973) who investigates corrective taxation when demand is a function of the externality, however, in our case, the direct effect always outweighs the indirect effect.

Furthermore, in the case of heterogeneous moral preferences, the Ramsey tax will increase with the positive correlation between income and clean good preference. This is because when preferences are cleaner, the morality term will be greater, and thus the indirect effect of an increase in demand following an increase in the dirty good tax would be greater (although still less than the direct effect of reducing demand). Since those with higher income will consume more of all goods, this makes the overall price elasticity of demand for the dirty good less elastic.

When we repeat this analysis for goods with positive environmental externalities, we obtain similar results. However, in this case, moral preferences make the demand for goods with positive externalities more elastic, $\varepsilon_Z = -\frac{1}{1+\frac{\sum_{h=1}^{H} m^h z^h}{Z}}$, consequently lowering the optimal level of Ramsey taxation.

1.4 Discussion

This paper has set up a model of optimal commodity taxation for dirty and clean goods with Kantian moral consumers. It has shown that when moral consumers are homogeneous, all environmental externalities are internalised, removing the need for corrective Pigouvian taxation. It has further shown that when moral consumers are heterogeneous, whilst they internalise a large degree of the environmental externalities, there is a residual externality arising from preference heterogeneity which requires a Pigouvian corrective tax. Furthermore, in both cases, moral preferences increase the price inelasticity of demand for the dirty good relative to the clean good, resulting in relatively higher Ramsey revenue-raising taxes. Overall, this suggests that in a system of optimal taxation with perfectly Kantian preferences, the corrective Pigouvian element will reduce whilst the revenue-raising Ramsey component will increase. The extent of changes to these components will depend upon the variance in preferences, and the correlation between preferences, demands and incomes. The relative changes of these two tax components will determine the overall influence of moral preferences on optimal tax rates. This remains an empirical question.

Whilst setting up our model, several key simplifying assumptions have been made. Firstly, we have assumed that all consumers are perfectly moral with regard to their consumption of the dirty good, resulting in the full internalisation of negative externalities when consumers are homogeneous. When choosing their consumption of the dirty good, they follow Roemer's (2010) rationale of Kantian optimisation, consuming at a level where they would not wish for all agents to deviate from their current consumption by any common multiplicative factor. However, in reality, consumers are not perfectly moral. Moral considerations are likely to be a relevant factor in their decision-making process, but this factor will generally be weighed against material and social factors. An individual might not do the perfectly moral thing if it were extremely costly or if it would go against a social norm or hurt someone they loved. Alger and Weibull (2013) and Eichner and Pethig (2022) include both material and moral preferences within the consumer's utility function. Brekke *et al.* (2003) and Long (2021) include both material preferences and moral preferences through a self-image payoff function. These representations of utility fit more closely with empirical findings, whereby moral behaviour is combined with both selfish and other-regarding or social preferences (Miettinen *et al.,* 2020; Van Leeuwen and Alger, 2021). We expect that as the degree of morality reduces, the degree of internalisation of external effects will reduce, and henceforth the optimum level of corrective taxation will increase. Simultaneously, we expect that a reduction in morality will increase responsiveness to changes in the market price. This increase in demand elasticity would imply that the optimum level of revenue-raising taxation will be reduced.

Secondly, whilst we have employed a general, Bergson-Samuelson social welfare function in the composition of the model, we simplified this to a utilitarian social welfare function in our model analysis and interpretation. Given the concavity of Cobb-Douglas utility functions, the linear, utilitarian Bergson Samuelson social welfare function implies a preference for redistribution. Whilst social welfare will increase by the same amount regardless of whether this is experienced by the lowest or the highest income household, lower income household will experience higher marginal utility from a given change in consumption. Cremer *et al.* (2003) demonstrate that when the government has equity concerns and consumers have heterogeneous preferences, Pigouvian taxation plays a redistributive role on top of its corrective mandate. It would be interesting to investigate how changing the weight of equity concerns influences optimal policy, we expect that the influence this has upon the environment will depend upon the correlation between income and household preferences.

Thirdly, we have assumed that every individual has the same marginal contribution to the pollution externality and that every individual suffers the same marginal damage from pollution. On the one hand, the demand of individuals may have different marginal contributions to external damages, for example, this may depend upon the energy efficiency of their technology or the way they dispose of waste after consumption. Diamond (1973) sets up a model within which consumers have different marginal contributions to pollution, he finds that the optimal tax depends on how sensitive different contributors to pollution are to changes in the price of the dirty good and the size of the externality. When those who have larger marginal contributions have demands that are more sensitive to the size of the externality, then a smaller corrective tax is optimal. In our model, the responsiveness of demand to external damages is captured within the morality term, therefore we would expect that if there was a positive correlation between the morality term and an individual's marginal contribution to damages, then a smaller corrective tax would be optimal, because those who have the highest potential to cause damage tend to make the greatest effort to internalise externalities.

On the other hand, individuals may experience different marginal damages from pollution due to living in different places, having different routines, different health conditions, and different abilities to mitigate damages. Sandmo (1975) sets up a model within which consumers experience different marginal damages from pollution. He finds that when lower-income individuals suffer higher marginal damages from pollution, the corrective element of optimal taxation is larger. Overall, Sandmo finds that the revenue-raising component of the tax is highest in the presence of high-income polluters, whilst the corrective component of the tax is highest in the presence of low-income pollutees. We expect these findings to carry over to extensions of our model. We confirm this in Appendix A4, where we introduce a household specific scale parameter on the damage function. For heterogeneous moral consumers, the corrective component of tax is highest when the scale of damages is positively correlated with higher income and negatively correlated with clean good preferences.

Extensions of our model could consider modifying the assumptions above. Additional extensions could consider broadening from a static framework to a dynamic framework. This would demonstrate the influence that morality may have on the market and optimal taxation over time. This could include how morality and preferences evolve over time and how firms respond to changes in preferences and tax rates. Also, the model could be extended to consider more general utility functions with non-zero cross price effects, such as a constant elasticity of substitution (CES) utility function, in this case the baseline Ramsey Rule would not hold, thus our point of comparison would change. However, it could offer broader insights to optimal commodity taxation.

Furthermore, we have taken an exclusively theoretical approach within this paper to investigate the channels through which optimal taxation would change in the presence of moral green consumers. In doing so I have worked exclusively in quantity-space, to facilitate direct comparisons with the baseline Ramsey Rule. Whilst this offers valuable insights into the uniformity/non-uniformity of Ramsey taxation and the need for Pigouvian taxation, it gives limited insights to the actual magnitude of optimal tax rates and the relative scales of Ramsey and Pigouvian tax. Further investigations would benefit from numerical simulations calibrated to real-world market data to investigate the magnitude of optimal taxation and the degree to which it changes in response to morality and household heterogeneity with different patterns of correlation between preferences and income.

The key takeaway from this paper is that internal moral motivations to internalise external damages arising from one's actions can significantly benefit the environment and that whilst external intervention is generally still necessary to maximise social welfare, the optimal intervention is likely to be significantly influenced by these internal moral motivations. Three policy recommendations arise from our findings. Firstly, higher taxes should be placed on dirty goods that are consumed disproportionately by higher income consumers; this will reduce the social cost of corrective taxes. Secondly, goods which are perceived with stronger moral connotations should have lower corrective taxes, since individuals tend to voluntarily reduce their consumption of these goods. Moral connections may be stronger when individuals can observe the damages caused by consumption or when they relate to the damages in a stronger way. Thirdly, information campaigns and public engagement programs can increase consumers' perception of their environmental impact and increase their engagement with the environment, highlighting the moral dimension of their actions hence activating moral propensities within their decision-making.

CHAPTER 2: Green Investment and Kantian Morality

Lucy Naga*, Thomas I. Renström, Laura Marsiliani

Abstract

The rise of responsible investment cannot be fully explained by standard utilitarian behaviour. While, moral theories have been applied to responsible consumption and voluntary provision of public goods, but no attempts have been made at modelling moral investments. This paper develops a model of Kantian moral investment, where agents seek to do the right thing by investing according to how they would want everyone to invest. We derive the first-best Pareto efficient asset pricing relation for this framework, which contains a pollution premium on dirty assets. We compare first-best outcome to the equilibria under non-Kantian, fully Kantian, and partially Kantian scenarios, highlighting the implications for equilibrium pollution levels. In a fully Kantian economy, the equilibrium is Pareto efficient, with wealth inequality and preference heterogeneity shaping portfolio holdings. However, when only a fraction of investors is Kantian, the equilibrium outcome depends on both the proportion of Kantians and the scope of their morality. Specifically, inclusive Kantians — who act on what they believe all agents, including non-Kantians, ought to do — generate more pollution than exclusive Kantians, who adjust their behaviour acknowledging that non-Kantians will not act similarly. As the proportion of non-Kantians increases, the equilibrium deviates further from the Pareto-efficient allocation. These findings provide new insights into the relationship between morality, investment behaviour and environmental outcomes.

JEL classification: D62; D64; G11; G12

Keywords: Kantian morality, Pollution, Ethical investment, Asset Pricing

Acknowledgements: We would like to thank participants of the European Association of Environmental and Resource Economics (EAERE) Annual Conference 2023, Limassol, Cyprus, and participants of the Energy Ethics 2023 Conferences, St Andrews, Scotland for their insightful comments.

*Corresponding author: Lucy Naga, Department of Economics Durham University Business School, Mill Hill Lane, Durham DH1 3LB, United Kingdom. Email: lucy.v.hyde@durham.ac.uk
Thomas I. Renström, Department of Economics Durham University Business School, Mill Hill Lane, Durham DH1 3LB, United Kingdom. Email: t.i.renstrom@durham.ac.uk
Laura Marsiliani, Department of Economics Durham University Business School, Durham Energy Institute and Durham Centre for Sustainable Development, Law and Policy, Mill Hill Lane, Durham DH1 3LB, United Kingdom. Email: laura.marsiliani@durham.ac.uk

2.1 Introduction

'I didn't see how divesting alone would stop climate change or help people in poor countries. It was one thing to divest from companies to fight apartheid, a political institution that would (and did) respond to economic pressure. It's another thing to transform the world's energy system...just by selling the stocks of fossil-fuel companies.

'I still feel this way today. But I have come to realize that there are other reasons for me not to own the stock of fossil-fuel companies — namely, I don't want to profit if their stock prices go up because we don't develop zero-carbon alternatives. I'd feel bad if I benefited from a delay in getting to zero.'

(Bill Gates, 2021, p 9-10).

These were the words of magnate and philanthropist Bill Gates, who in 2019, divested all direct holdings in oil and gas companies[1]. The above quote demonstrates the moral concerns of investors, who seek to do the right thing despite their individual actions having negligible tangible effects on the state of the environment and climate.

Socially responsible investment (SRI) is on the rise. SRI may be defined as a 'long-term oriented investment approach, which integrates environmental, social and governance (ESG) factors in the research, analysis, and selection process of securities within an investment portfolio' (Eurosif 2016, p.9). In 2021, a record $649 billion poured into ESG-focused funds worldwide, up from $542 billion and $285 billion in 2020 and 2019. ESG funds now account for 10% of worldwide fund assets (Reuters, 2021). Research by OnePlanetCapital (2022), a new sustainability-driven investment house, found that 85% of investors now view climate change as the greatest long-term threat, and many have begun to move their investments in response. They report that 12% plan to transfer into 'ESG' funds this year, and 17% plan to do so in the next few years. Meanwhile, 70% of investors say they would actively avoid putting money into companies with a negative environmental impact.

In a report investigating the perspective of asset owners, Morningstar Sustainalytics (2023) found that the three greatest drivers of ESG investing are senior management/leadership (around 36% of the 500 interviewed asset owners rated this in their top 3 motivations), ethical and moral principles (around 31%), and external pressures from media and campaign groups (around 27%). This suggests that reputation, morality, and social pressure are significant drivers of ESG investing. Meanwhile, the report finds that the principal barrier to pursuing an ESG investment strategy is the impact on returns (around 38% rated this in their top 3 barriers). This implies that asset owners may face a trade-off between traditional investment objectives of maximising risk-adjusted returns, and the moral and social pressures of doing the right thing for the environment and society. Indeed, empirical literature

[1] As did the trust that manages the Gates Foundation's endowment.

demonstrates this trade-off, with socially responsible portfolios generating lower returns than conventional alternatives but delivering external benefits in the form of ESG contributions (Baker *et al*., 2022; Barber *et al.,* 2021; Zerbib, 2019).

Two key theories seek to explain why socially responsible portfolios tend to generate lower returns: the climate risk theory and the investor preference theory. The climate risk theory states that firms with stronger ESG performances are more resilient to future climate risk, including both physical damages from climate change and policy implications of climate change legislation. Thus, investors have a higher willingness to invest in firms with higher ESG scores to hedge against this risk (Ardia *et al.,* 2022; Bolton and Kacperczyk, 2021; Ilhan *et al.,* 2021; Engle *et al.,* 2020; Ceccarelli *et al.,* 2023). The investor preference theory states that investors derive non-pecuniary benefits from contributing funds towards ESG factors, and thus have a higher willingness to invest in funds which have greater ESG impact.

Both theories are supported by the empirical literature. Both theories suggest that investors would be willing to accept lower financial returns from socially responsible firms (Pástor *et al.,* 2021; Barber *et al.,* 2021; Zerbib, 2019; Hong and Kacperczyk, 2009).

The climate risk theory further implies that in times of economic or environmental crisis, socially responsible firms should outperform conventional firms due to their greater resilience. This has been found during the 2008-2009 financial crisis (Lins *et al.,* 2017), the COVID-19 crisis (Albuquerque *et al.,* 2020; Pástor and Vorsatz, 2020), when there were unexpected increases in climate change concerns (Ardia *et al.,* 2022) or the salience of climate change (Choi *et al.,* 2020).

The investor preference theory further implies that money flowing into socially responsible funds should be less sensitive to changes in risk-adjusted returns (Renneboog *et al.,* 2008). Bollen (2007) finds this is the case, with demand for socially responsible firms being less volatile than demand for conventional funds, and demand being less responsive to poor returns than to good returns. This asymmetry of elasticity indicates the commitment and loyalty of socially responsible investors towards the ESG elements of their investment portfolio. The investor preference theory is further supported by empirical studies seeking to elicit investor's preferences and motivation. In a field study, Bauer *et al.* (2021) found that two-thirds of pension fund members voted for the fund to expand engagement with companies based on their commitment to sustainable development goals, even when they expect that this will hurt financial returns. Bauer *et al.* (2021) employ Falk *et al.'s* (2018, 2023) empirically validated measure of social preferences to demonstrate that these are a key driver of the observed socially responsible behaviour. Furthermore, Bonnefon *et al.* (2022) and Hartzmark and Sussman (2019) use experimental settings to characterise the moral concerns and environmental concerns of investors, Bonnefon *et al.* (2022) demonstrate strong evidence that investors seek to align their investments with their social values, meanwhile Hartzmark and Sussman (2019) find that investors who consider environmental and social impact when making their investments respond to an environmental information shock more than performance and risk expectations could account for. This suggests that whilst ESG factors can influence both the expected risk and return of investments, patterns of risk and return are not sufficient to capture patterns of socially responsible behaviour, therefore, consideration of non-pecuniary preferences is necessary.

Non-pecuniary preferences refer to preferences for any non-financial aspect of an investment. For socially responsible investments, investors may be environmentalists who explicitly place value on the environmental outcomes, they may be altruists who value the social and governance outcomes and care about the wellbeing of others. However, in many cases, an individual's investments have a negligible effect on the overall performance of the firm and subsequent environmental and social outcomes. Andreoni (1990) introduces the concept of 'impure altruism' whereby individuals derive private value from the act of contributing to a public good, independent of the benefits they derive from the good itself. This detaches the non-pecuniary benefit from expected consequences, with agents modelled to derive a 'warm glow' from doing a good thing. This warm glow concept has been adopted widely within the theoretical literature for public good contributions and socially responsible investment. The utility function of socially responsible investors has been enriched with a warm glow derived from the observed social impact of firms they invest in (Pástor *et al.,* 2021), the environmental score of their portfolio (Baker *et al.,* 2022), pollution flows caused by firms they hold shares in (Dam and Heijdra, 2011; Dam, 2011), and the perceived pollution content of their investment portfolio (Dam and Scholtens, 2015; Renström *et al.,* 2019, 2021). These theoretical models demonstrate that warm glow preferences result in a pollution premium being charged on polluting or socially damaging firms, this pushes up their cost of capital, thus reducing their production and the production of negative externalities, whilst incentivising investment in abatement activities. Renström *et al.* (2019, 2021) investigate the policy implications of warm glow preferences. They find that the warm glow preferences reduce the optimal corrective tax needed to internalise the negative externalities of pollutive firms, meanwhile, they make the policy of subsidising abatement activities more effective.

We seek to further enrich investor preferences to incorporate the mechanisms underlying this warm glow payoff. Andreoni *et al.* (2017, p.626) claim that 'the concept of warm glow is a placeholder for more specific models of individual and social motivations'. It is important to consider specific motivations because different motivations operate through different mechanisms and respond differently to policy changes. Since the term SRI is used interchangeably with moral/ethical investing and is often conceptualised as investors seeking to do the right thing for the environment and society, we focus on the moral motivations of investors. As Chapter 1 highlights, philosophy presents a plethora of moral theories, from egoistic consequentialism underlying the selfish behaviour of neoclassical models to altruism which broadens the scope of consequentialist concern to the wellbeing of others, and from deontology which abstracts from consequences and seeks to follow moral rules to virtue ethics whereby individuals seek to be a good person. Due to the negligible effect of an individual investor's portfolio on realised outcomes and the complexity of defining a good person, we draw on the deontological philosophy of Kant to determine the 'right' behaviour. Kant's moral rule, the categorical imperative, states that one should,

"Act only according to that maxim whereby you can, at the same time, will that it should become a universal moral law"

(Kant, 1785, 4:421 as in Koorsgaard 2012, p34).

This can be interpreted as setting out a logical relation that one should only engage in an action if they can consistently wish that others do the same thing if they were in the same situation. Laffont (1975) introduced this concept within the economics literature, and it has been employed within theoretical modelling in public goods (Brekke *et al.,* 2003, Alger and Weibull, 2013; Roemer, 2010, 2019; Long, 2021) and green consumerism literatures (Eicher and Pethig, 2022).

Our paper proceeds as follows. The literature review in section 2.2 covers the formalisation of Kantian moral preferences within economics and highlights the relevance of moral preferences for SRI. Section 2.3 presents our asset pricing model in the presence of environmental externalities and Kantian moral investors. Section 2.4 reports simulation results from our partial Kantian models. Section 2.5 discusses our findings and concludes. We will seek to answer the two questions raised by Marsiliani *et al.* (2023), firstly, would non-standard preferences enable an efficient equilibrium to be achieved whereby externalities from production are internalised? Secondly, if government intervention is needed, what is the nature of this intervention under these non-standard preferences?

2.2 Literature Review

Marsiliani *et al.* (2023) highlight that enriching the behaviour of economic agents beyond neoclassical representations is necessary in the presence of market failures. Neoclassical behaviour is sufficient when agents have full information about the consequences of their actions; prices are set at marginal costs and are reliable signals of value; and markets are complete with all consequences appropriately priced. However, the ESG factors of investments represent a positive external effect which is not adequately accounted for within the market, therefore, neoclassical models of investment behaviour diverge from observable behaviour. Edgeworth (1881) recognises that whilst his statement that 'the first principle of Economics is that every agent is actuated only by self-interest' was appropriate for agents engaging in 'economical calculus' (exchange in a perfectly competitive market), it is fundamentally mistaken about general human behaviour (Sen, 1977). In the presence of externalities, motivation diversifies beyond self-interest. Social norms, community values, and moral rules which guide non-economic behaviour play an important role in much of economic life. ‘A close look reveals that a great deal of economic life depends for its viability on a certain limited degree of ethical commitment. Purely selfish behaviour of individuals is really incompatible with any kind of settled economic life.’ (Arrow, 1973, p.314).

2.2.1 Warm Glow Preferences

The ‘warm glow’ approach to modelling non-standard investor preferences is the first step. Andreoni (1990) introduced the concept of ‘warm glow’, suggesting that agents derive a private benefit from the act of contributing to a public good which is separate from the benefit derived from the public good itself. Ziven and Small (2005) suggest that in the context of investment, socially responsible investors perceive the firm’s managers to act on their behalf, and thereby derive a warm glow payoff from the act of contributing to public goods through holding securities issued by socially responsible firms. Similarly, in the context of environmental externalities, Dam (2011) models socially responsible investors to feel partly responsible for the pollution generated by firms in which they hold shares, thus they derive a negative warm glow payoff from investing in dirty firms. Warm glow models of SRI demonstrate that a premium is demanded on returns from firms generating negative environmental or social externalities (Dam, 2011; Dam and Heijdra, 2011; Renström *et al.,* 2019, 2021), or that investors are willing to receive lower returns from socially responsible firms (Baker *et al.,* 2022; Pástor *et al.,* 2021; Zivin and Small, 2005). This makes the cost of capital more expensive for ‘bad’ firms, reducing production and reducing negative externalities; meanwhile ‘good’ firms can access cheaper capital and their production is promoted. This reduces social and environmental harm both through shifting funding towards socially responsible firms, and through creating a financial incentive for ‘bad’ firms to invest in abatement activities and contribute to ESG factors. Whilst warm glow preferences bring investment closer to the Pareto optimum, government intervention is still necessary to internalise externalities from production.

Renström *et al.* (2019, 2021) investigate the policy implications of warm glow preferences on optimal corrective taxation and optimal subsidies for abatement activities. Renström *et al.* (2019) demonstrate that warm glow preferences operate like an implicit tax, by raising the cost of capital for harmful firms. Subsequently, the optimal level of explicit corrective tax is lower in the presence of warm glow investors. Renström *et al.* (2021) investigate whether policy can be designed such that environmental performance can be improved without the trade-off of lower economic performance, as is the case with corrective taxation. They investigate the role of abatement subsidies which can allow firms to increase production but reduce the negative environmental or social impact of production per unit. They demonstrate that warm glow preferences are key to the effectiveness of abatement subsidies since firms engaging in abatement would be rewarded by investment from warm glow investors with lower/no premiums charged. Therefore, the nature of government intervention changes in the presence of warm glow preferences, with optimal tax lowering and abatement subsidies becoming viable.

2.2.2 Moral Preferences

Socially responsible investors are often conceptualised as being 'ethical' or 'moral', due to them seeking to bring about beneficial social and environmental outcomes (Lewis and Cullis, 1990). Brooks (1989, p32) defines ethical investors as those who 'believe that all investments they make have an ethical dimension, that they can and should apply their ethical standards to potential investments… they look for an investment vehicle with both ethical and financial quality'. This matches the claim Laffont (1975, p.431) makes that 'every economic action takes place in the framework of a moral or ethics', and Arrow's (1973) earlier statement on the importance of ethical commitment in economic life.

Marsiliani *et al.* (2023) argue that within the context of externalities and interdependent agents, the concept of morality in economics must be expanded beyond the egoistic consequentialist represented within neoclassical models. They highlight how the economics literature tends to draw on Kantian morality as an alternative since this broadens the scope of morality beyond the individual and moves the focus away from the expected consequences of actions to the rightness or wrongness of the actions themselves. A socially responsible investor can then be modelled to seek to do the right thing and to put their money where their values lie.

Kantian morality is based on the principle that one should "Act only according to that maxim whereby you can, at the same time, will that it should become a universal moral law" (Kant, 1785, 4:421 as in Koorsgaard 2012, p34). This concept has been introduced into the economics literature and interpreted to mean that the economic agent should consider the Kantian counterfactual of what would happen if everyone were to behave similarly and then optimise their consumption accordingly. Henceforth, the Kantian agent would be motivated to internalise the externalities arising from their own actions by seeking to reduce the externalities imposed upon them by other agents. This behavioural motivation has been found to be evolutionarily conceivable for economic agents (Bergstrom, 1995; Curry and Roemer, 2012; Alger and Weibull, 2013, 2016; Alger *et al.,* 2020), and to be empirically validated within various economic scenarios (Elias *et al.,* 2016; Czajkowski *et al.,* 2017; Caparo and Rand, 2018; Miettinen *et al.,* 2020; Van Leeuwen and Alger, 2021), whereby moral preferences are often found to operate alongside material and social preferences.

Morality has not been formally modelled within the investment literature; therefore, we draw on examples from the public goods literature and green consumerism literature to construct our model. Kantian morality has been introduced in various ways, both for identical and heterogeneous consumers, both directly and indirectly.

When agents are identical, with the same preferences and constraints, the Kantian counterfactual is the hypothetical scenario of all agents performing the same action as the decision maker. Alger and Weibull's (2013) model of the homo moralis represents agents to have utility functions which are a convex combination of material utility which employs the Nashian counterfactual and moral utility which employs the Kantian counterfactual. Brekke *et al*. (2003) model agents to calculate the Kantian moral ideal according to the Kantian counterfactual, they subsequently represent utility to be a weighted sum of material utility and a self-image payoff which is determined by how close their action is to their moral ideal.

When individuals are heterogeneous, with different preferences and/or constraints, the Kantian counterfactual must be adjusted. The hypothetical scenario of all agents acting according to the 'same maxim' would no longer imply that agents will perform the same action. Roemer (2010) suggests that the 'same maxim' may be interpreted as agents deviating from their current action by the same multiplicative factor. Thus, Roemer suggests that the Kantian equilibrium is where 'no player would like all players to alter their contributions by the same multiplicative factor' (Roemer, 2010, p1). Roemer models an economy of perfect Kantians and finds that in the Kantian equilibrium, the Pareto efficient outcome is achieved. Long (2021) integrates Roemer's (2010) model of heterogeneous moral optimisation into Brekke *et al.'s* (2003) framework of partial morality, to investigate the role of self-image underpinned by heterogeneous moral ideals.

Models of partially moral agents facilitate investigation into how an individual's degree of morality influences consumption. A further extension to the literature considers how agents with moral preferences interact with non-moral agents, and how their Kantian counterfactual takes the presence of non-moral agents into account (Long, 2016, 2017, 2019; Grafton *et al.,* 2017). Within these papers, Long distinguishes between inclusive and exclusive Kantians; inclusive Kantians would consider all agents, Kantian and non-Kantian, to be hypothetical co-movers within their Kantian counterfactual, whilst exclusive Kantians would only consider the subset of Kantian agents to be co-movers, taking non-Kantian actions as given. Long (2019) also considers a continuum of inclusivity between these two extremes, with Kantians considering non-Kantians to deviate by some fraction of the multiplicative factor. He finds that when Kantians and non-Kantians interact, non-Kantians will out-perform Kantian agents, but the pay-off of both agents will increase both in the share of Kantian agents and in the degree of inclusivity of these Kantians, whilst the size of the externality will decrease with both parameters. It would seem that inclusive Kantianism is a better reflection of Kant's maxim of a universal moral law, however, exclusive Kantianism may reflect a greater degree of realism regarding the practice of Kantian morality.

The literature has shown that in the context of public goods and green consumerism, Kantian agents can achieve an efficient equilibrium if all agents are identical and perfectly Kantian (Roemer, 2010; Chapter 1 of this thesis). If agents are partially Kantian then their morality brings the economy closer to the efficient equilibrium but does not fully internalise externalities (Brekke *et al.,* 2003; Eichner and Pethig, 2022). Furthermore, in chapter 1 we demonstrate that even if all agents are perfectly Kantian, if they have heterogeneous preferences then the equilibrium falls short of the Pareto optimum.

This implies that, so long as agents are either heterogeneous or imperfectly moral, government intervention is needed. Brekke *et al.* (2003) highlight the importance of considering consumer perception of policy intervention, and the potential for moral motivations to be crowded out by shifting the locus of responsibility onto the government. On the one hand, if a corrective tax is perceived to cover the full social cost of an externality, moral motivation would be crowded out. Whilst this is acceptable when the perception is correct, if the tax does not actually cover the full social cost, the equilibrium will be sub-optimal. Dasgupta *et al.* (2016) argue that a Pigouvian tax covering the full social cost of the externality would be necessary since when individuals have heterogeneous degrees of morality and individual-specific taxes are infeasible, the only way to achieve the Pareto optimum is to crowd out the existing moral motivation and impose external policy stimulus.

On the other hand, Brekke *et al.* (2003) highlight that when taxes are perceived as a symbolic punishment which reminds people that such behaviour is harmful but does not cover the full social cost of the externality, then the tax can crowd in moral motivation. This is supported by Eichner and Pethig (2022), who find that whilst individual-specific taxes would be ideal in the first-best world, the second-best tax policy would be a uniform tax which is smaller than the Pigouvian tax. This demonstrates that a combination of morality and external policy intervention can complement one another to realise the social optimum. Brekke *et al.'s* (2003) theory on crowding in moral motivation supports Frey and Stutzer's (2008) view on the importance of self-determination and endowing moral responsibility to agents. Therefore, overall, models of morality suggest that not only should optimal taxation be lower, but that it is important to consider individual's perception of the policy and their feeling of responsibility.

In what follows, we adopt Roemer's (2010, 2019) representation of Kantian morality to model moral investors who optimise their investment portfolio. We subsequently adopt Long's (2016, 2017, 2019) representation of inclusive and exclusive Kantian agents to model the influence of moral investors in a market which also contains non-moral investors.

2.3 Model

We consider a two-period, lifecycle asset-pricing model. We model households, $h = 1, \ldots H$, to derive utility from their consumption in both periods, $\{c_1^h, c_2^h\}$, and disutility from pollution, X. The utility function is assumed to be additively separable in these arguments,

$$U^h = u(c_1^h) + \beta[u(c_2^h) - \eta^h v(X)], \tag{2.1}$$

where β is the intertemporal discount factor and η^h measures the household's preference for the environment. We assume that $u(.)$ is an increasing, concave function, and $v(.)$ is an increasing, linear function.

In period 1, households earn labour income, l_1^h, where the first period exogenous wage rate is normalised to unity. They spend this income on consumption, c_1^h, and investment $\{k^h, z^h\}$, subject to the constraint,

$$l_1^h = c_1^h + k^h + z^h. \tag{2.2}$$

Their investment portfolio consists of investment in a 'clean' firm, k^h, and investment in a 'dirty' firm, z^h. The dirty firm generates pollution which causes disutility.

In period 2, households earn labour income, wl_2^h, and income from the return on their investments, $\{Rk^h, Pz^h\}$. They spend this income on consumption, c_2^h, subject to the constraint,

$$c_2^h = wl_2^h + Rk^h + Pz^h. \tag{2.3}$$

Here, w is the second-period endogenous wage (defined below), R is the constant return on clean investment, and P is the return on dirty investment defined below by the dirty firm's production function. The return on dirty investment is determined by the dirty firm's production and subsequent profits.

The dirty firm uses the invested capital, $Z = \sum_h z^h$, and hires exogenously supplied labour, $L = \sum_h l_2^h$, to produce output according to a constant return to scale production function, $F(Z, L)$. The firm earns profit,

$$\pi = \max_L F(Z, L) - wL \,. \tag{2.4}$$

The firm's first order condition at the optimal production level determines the wage rate,

$$F_L(Z, L) - w = 0. \tag{2.5}$$

A household's investment of z^h implies that they earn a share $\frac{z^h}{Z}$ of the profits. Consequently, shareholder income is $\frac{\pi z^h}{Z}$ and the return is,

$$P = \frac{\pi}{Z}. \tag{2.6}$$

The polluting firm generates pollution, X, which we assume to be linear in production,

$$X = \psi F(Z, L). \tag{2.7}$$

The first-period resource constraint is given by aggregating consumers' first-period budget constraint (eq. 2.2),

$$\sum_h l_1^h = C_1 + K + Z. \tag{2.8}$$

The second-period resource constraint is given by aggregating consumers' second-period budget constraint (eq. 2.3) using the definition for P, and substituting in the firm's profit function (eq. 2.4),

$$C_2 = w \sum_h l_2^h + RK + F(Z, L) - wL = RK + F(Z, L). \tag{2.9}$$

2.3.1 Pareto Efficiency

Pareto efficient investment requires that it is not possible to increase the utility of one household without lowering the utility of other households. Consequently, to derive the Pareto efficient asset-pricing rule we seek to maximise the utility of a given household, (eq. 2.1 for $h = 1$) keeping all other households' utilities (eq. 2.1 for all $h \neq 1$) above certain threshold values, subject to the resource constraints (eq. 2.8 and 2.9). The Lagrange function for this optimisation problem is,

$$\begin{aligned}\mathcal{L} &= u(c_1^1) + \beta\left[u(c_2^1) - \eta^1 v\big(\psi F(Z,L)\big)\right] \\ &+ \sum_{h=2}^{H} \mu^h \left\{u\big(c_1^h\big) + \beta\left[u\big(c_2^h\big) - \eta^h v\big(\psi F(Z,L)\big)\right] - \bar{U}^h\right\} \\ &+ \lambda_1 \left\{\sum_{h=1}^{H} \big(l_1^h - c_1^h\big) - K - Z\right\} + \lambda_2 \left\{RK + F(Z,L) - \sum_{h=1}^{H} c_2^h\right\}. \qquad (2.10)\end{aligned}$$

Notice that only the aggregate investments are relevant here. The Lagrangian multipliers, μ^h, λ_1, and λ_2 correspond to the 'tightness' of the utility and resource constraints. The exact allocation will be a function of those constraints; however, we can derive an efficiency rule which holds regardless of the constraints. The efficiency rule corresponds to the Samuelson (1952) Rule for Pareto Efficient public goods provision. In our case, we have an asset-pricing rule (see Appendix B1 for derivation[2]):

Proposition 1: *The externality, X, is Pareto Efficient if and only if the return on investment in the polluting industry obeys:*

$$F_z(Z,L) - R = \sum_{h=1}^{H} \eta^h \frac{v'(X)}{u'\big(c_2^h\big)} \psi\, F_z(Z,L) \ . \qquad (2.11)$$

Proposition 1 states that the difference between the return on the polluting asset, F_z, and the clean asset, R, is equal to a pollution premium. The pollution premium is determined by the marginal social cost of pollution and is the sum of the marginal rates of substitution between the environment and private consumption, multiplied by the asset's marginal pollution. The stronger households' preferences are for the environment, the larger the pollution premium will be.

A higher pollution premium will increase the cost of capital for the dirty firm. This reduces the level of production which lowers the amount of pollution emitted.

2.3.2 Competitive Equilibrium in the Absence of Kantian Investors

In the competitive Walrasian equilibrium under 'standard' preferences and individualistic behaviour, each investor will maximise their utility holding the utility of all other investors constant. Since each household is small in comparison to the market, their investment decisions will have a negligible impact

[2] Given that we cannot have negative capital in a closed economy, Appendix B1 applies the constraint that $K \geq 0$. We calculate the Pareto optimal asset pricing rule when this constraint is binding and when it is non-binding. We assume that it is non-binding throughout the paper.

on the production of firms, and thus on the overall level of pollution. Consequently, from the households' point of view the two assets, K and Z, will be equivalent and must yield the same return.

This can be demonstrated by modelling each household to choose their investment portfolio to maximise their intertemporal utility function (equation 2.1) subject to their resource constraints (equations 2.2 and 2.3),

$$\mathrm{Max}_{k^h,z^h} U^h = u\left(l_1^h - k^h - z^h\right) + \beta\left[u\left(wl_2^h + Rk^h + \frac{F(Z,L) - wL}{Z} z^h\right) - \eta^h v\left(\psi F(Z,L)\right)\right]. \quad (2.12)$$

This gives the first-order condition Euler equations,

$$\frac{\partial U^h}{\partial k^h} = -u'\left(c_1^h\right) + \beta R u'\left(c_2^h\right) = 0, \quad (2.13)$$

$$\frac{\partial U^h}{\partial z^h} = -u'\left(c_1^h\right) + \beta\left(\frac{F(Z,L) - wL}{Z}\right) u'\left(c_2^h\right) = 0. \quad (2.14)$$

Given the Euler equations (Eq. 2.13 and 2.14) and given that constant returns to scale production implies $P = \frac{F(Z,L)-wL}{Z} = F_Z(Z,L)$ (see Appendix B2), we can see that,

$$R = F_Z(Z,L) = P. \quad (2.15)$$

Here there is no pollution premium, the return is equal across investments.

In the 'standard' competitive equilibrium, the marginal product of the dirty firm is equal to the gross return of the clean asset and thus lower than the Pareto efficient level, implying that pollution is sub-optimally high.

2.3.3 Equilibrium in the Presence of Kantian Investors

Kantian moral investors optimise their investment decisions according to Kant's categorical imperative; thus, they consider what would happen if all other investors were to behave similarly to them and optimise their payoff in this Kantian counterfactual scenario. We adopt Roemer's (2010, 2019) formalisation of Kantian morality, representing the 'same maxim' within the categorical imperative as the 'same multiplicative deviation' from current investment levels.

Note that Kantian optimisation is only relevant for the choice of the dirty investment since this is the only decision which exhibits externalities whereby each investor is impacted by the investment decisions of all other investors. In the case of private consumption and clean investments, household decisions are independent and thus Kantian optimisation would coincide with conventional, neoclassical optimisation.

2.3.3.1 All Households are Kantian Investors

When all households are Kantian investors, each household would consider changing their dirty asset investment decision if they would gain higher private utility from all households changing their dirty asset investment by the same multiplicative factor. We notice that this is an equilibrium concept, whereby the Kantian equilibrium is reached when scaling the investment of all households by a common factor does not result in a utility gain for the household in question.

Therefore, households can be represented to maximise their intertemporal utility function (eq. 2.1) subject to their period 1 and period 2 budget constraints (eq. 2.2 and 2.3), assuming that all households are deviating from their dirty asset investments by a common multiplicative factor, γ^h.

Thus, the first-order condition with respect to the dirty investment is derived by maximising,

$$U^h = u\left(l_1^h - k^h - \gamma^h z^h\right) + \beta\left[u\left(wl_2^h + Rk^h + \frac{\gamma^h z^h}{\gamma^h Z}\left[F\left(\gamma^h Z, L\right) - wL\right]\right) - \eta^h v\left(\psi F\left(\gamma^h Z, L\right)\right)\right], \quad (2.16)$$

with respect to the factor of deviation, γ^h, and evaluating at the point where the household would not wish for any household to deviate by any common factor, $\gamma^h = 1$. This gives the Kantian first-order condition,

$$\left.\frac{\partial U^h}{\partial \gamma^h}\right|_{\gamma^h=1} = -u'\left(c_1^h\right)z^h + \beta\left[u'\left(c_2^h\right)z^h F_Z(Z,L) - \eta^h v'(X)\psi F_Z(Z,L)Z\right] = 0. \quad (2.17)$$

The first-order condition with respect to clean investment gives the usual consumption Euler equation,

$$-u'\left(c_1^h\right) + \beta R u'\left(c_2^h\right) = 0. \quad (2.18)$$

Combining these two first-order conditions gives the efficiency rule for a Kantian household,

$$z^h(F_Z(Z,L) - R) = \eta^h \frac{v'(X)}{u'(c_2^h)} \psi F_Z(Z,L)Z \,. \tag{2.19}$$

Aggregating this across all households gives the Pareto efficient asset-pricing rule in equation 2.11.

Proposition 2: *The Kantian equilibrium is Pareto Efficient; the externality is internalised.*

Thus, if all investors are Kantian, the externality problem is solved, and government intervention is not needed. This arises because Kantian investors calculate that the right thing is to reduce their own investments in the dirty firm since they would be better off if all households reduced their investments in the dirty firm. When all households are Kantian, this internalises the pollution externality.

Heterogeneity among Kantian investors implies that they choose different portfolio holdings.

Proposition 3: *Wealthier individuals will hold a larger share in the pollutive firm. Individuals with stronger preferences for the environment will also hold a larger share in the pollutive firm*[3].

Households with more productive labour will be richer and thus, assuming period 2 consumption is a normal good, they will achieve higher consumption in period 2. This implies a lower marginal utility of consumption and thus the right-hand side of their efficiency rule in equation 2.19 will be larger. Therefore, they will hold a larger share of investment in the polluting firm.

Households with stronger preferences for the environment, η^h, will also tend to hold a larger share of investment in the pollution firm. The exact relation between η^h and z^h depends upon the shape of the marginal utility function, Appendix B3 demonstrates that a sufficient condition for higher η^h to result in higher z^h is that the Arrow-Pratt measure of relative risk aversion is no greater than 1, i.e., $-\frac{u''(c_2^h)c_2^h}{u'(c_2^h)} \leq 1$. Whilst environmentalists having more dirty assets seems counterintuitive, it arises as a consequence of being in equilibrium. Kantian investors are seeking to balance the gain from a cleaner environment when everyone reduces their investment, against the loss of return on investment from reducing their own investment. Households with stronger environmental preferences, 'environmentalists', experience greater damages from pollution, and thus demand a higher pollution premium to compensate them for these damages. However, in equilibrium, the law of one price dictates that the pollution premium is the same for all households, and thus below the optimum level for environmentalists. Therefore, the Kantian environmentalist would need to hold larger shares in the

[3] Given the sufficient condition $-\frac{u''(c_2^h)c_2^h}{u'(c_2^h)} \leq 1$.

polluting firm in order for the loss of return from investment to balance the gain from a cleaner environment when everyone reduces their investment.

2.3.3.2 A Fraction of Households are Kantian Investors

When an economy is composed of both Kantian and non-Kantian investors, the Kantian investors will optimise according to their moral principles, whilst non-Kantians will behave competitively. Thus, Kantian investors will induce a pollution premium on dirty assets. Meanwhile, for non-Kantian investors, the polluting asset becomes dominant as it offers a higher return. This means that non-Kantian investors will invest only in the polluting asset. The size of the pollution premium and the scale of aggregate investment in the dirty firm will depend upon the proportion of Kantians and non-Kantians in the economy and the size of their savings.

In principle, one could have an equilibrium where non-Kantian investors invest up to the point where returns on clean and dirty assets are equalised, $F_z(Z^n, L) = R$, where Z^n denotes the total assets of the non-Kantians. In this case, non-Kantians could invest in both clean and dirty assets. Meanwhile, Kantian investors would be in a corner solution (equation 2.13 would be negative), in the sense that they seek to make a negative investment in dirty assets. Since this is not possible, they would hold only clean assets. This equilibrium would coincide with the 'standard' competitive equilibrium in section 2.2 above. However, if the savings of the non-Kantian are not enough to reach $F_z(Z^n, L) = R,$ then the Kantian investors play a role. Non-Kantians would invest solely in the polluting asset when $F_z(Z^n, L) > R$.

Long (2019) highlights two ways of modelling Kantians when non-Kantians are present — exclusive Kantians and inclusive Kantians. An exclusive Kantian would account for the fact that a proportion of investors are non-Kantian and would consider the right action as the best that Kantians can achieve within this environment. Thus, the exclusive Kantian counterfactual considers non-Kantian investors' behaviour to be constant whilst only Kantian households are considered as hypothetical co-movers. An inclusive Kantian would consider that they should do the moral action, even if others do not follow the moral view. Thus, the inclusive Kantian counterfactual considers both Kantian and non-Kantian households to be hypothetical co-movers in their Kantian optimisation.

We investigate exclusive and inclusive Kantian equilibria separately. Intuitively, we would expect the pollution premium to be lower in both equilibria than in a fully Kantian economy because Kantians have less market power to demand a premium, whilst non-Kantians will increase their investment in dirty assets in response to a premium causing it to decline further. We first derive the exclusive Kantian equilibrium and then the inclusive Kantian equilibrium, investigating how the presence of non-Kantians influences total investment in dirty assets.

2.3.3.2.1 Exclusive Kantians

First, we look at the case of exclusive Kantianism. In this optimisation, the Kantians assume non-Kantian behaviour to be constant whilst considering other Kantians to deviate by a common factor, γ^h. Exclusive Kantians would now choose their investment portfolio to optimise,

$$\begin{aligned} U^h = {} & u\left(l_1^h - k^h - \gamma^h z^h\right) \\ & + \beta\left[u\left(wl_2^h + Rk^h + \frac{F\left(\gamma^h Z^k + Z^n, L\right) - wL}{\gamma^h Z^k + Z^n}\gamma^h z^h\right) - \eta^h v\left(\psi F\left(\gamma^h Z^k + Z^n, L\right)\right)\right]. \end{aligned} \tag{2.20}$$

The exclusive Kantian first-order condition for the dirty investment would be,

$$\left.\frac{\partial U^h}{\partial \gamma^h}\right|_{\gamma^h=1} = -u'\left(c_1^h\right)z^h + \beta\left[u'\left(c_2^h\right)F_z z^h - \eta^h v'(X)\psi F_Z(Z,L)Z^K\right] = 0, \tag{2.21}$$

whilst the same Euler equation (eq. 2.18) would hold for the clean investment. These can be combined to give,

$$z^h(F_z - R) = \eta^h \frac{v'(X)}{u'\left(c_2^h\right)}\psi F_Z Z^K. \tag{2.22}$$

When aggregated over Kantian agents, this gives the overall pollution premium,

$$F_Z - R = \sum_{h\in\{Kant\}} \eta^h \frac{v'(X)}{u'\left(c_2^h\right)}\psi F_Z\ . \tag{2.23}.$$

Equation 2.23 suggests that the pollution premium is smaller than the Pareto efficient pollution premium, since it sums the marginal rates of substitutions among Kantian households only, without re-scaling. However, it would also depend upon the relative changes in the marginal utility gained from a Kantian increasing their own investment versus the marginal disutility experienced from all Kantian agents increasing their investment.

We verify that the exclusive Kantian pollution premium is lower than the Pareto optimal premium in Appendix B4.2, by taking to total differential of equation 2.23 to find how the overall level of dirty investment changes with the proportion of non-Kantians.

$$\frac{dZ}{d\delta} = \frac{\left[-\frac{N\eta\psi v}{u'(c_2^h)} - \frac{(N-N^n)\eta\psi v}{u'(c_2^h)}\frac{u''(c_2^h)}{u'(c_2^h)}\frac{\tilde{\beta}}{N}D\right]}{\left[\frac{F_{ZZ}R}{F_Z F_Z} + \frac{(N-N^n)\eta\psi v}{u'(c_2^h)}\frac{u''(c_2^h)}{u'(c_2^h)}\frac{\tilde{\beta}}{N}B\right]} > 0, \tag{2.24}$$

where $\delta = \frac{N^n}{N}$, $B = \left(F_{ZZ}\left(-Z + \frac{Z^k N}{N^k}\right) + \frac{F_Z - R}{(1-\delta)}(1 - Z^n F_{ZZ}A)\right) > 0$, and $D = \frac{(F_Z - R)}{(1-\delta)}\left(\frac{Z^k N}{N^k} - \frac{Z^n N}{N^n}\right) < 0$. We find that the analytical solution has a positive sign[4], demonstrating that in an economy with exclusive Kantians, as the proportion of non-Kantians rises, the level of investment in the dirty firm will rise.

Proposition 4: *In the Exclusive Kantian equilibrium, pollution is greater than in the Pareto efficient equilibrium.*

<u>*2.3.3.2.2 Inclusive Kantians*</u>

Next, we consider the case of inclusive Kantianism. In this optimisation, the Kantians consider both Kantians and non-Kantians to deviate by a common factor. Thus, the inclusive Kantians optimise equation 2.16, just as in the case where all agents are Kantian, resulting in each Kantian agent demanding a pollution premium as in equation 2.18. These premiums are then aggregated over the Kantian households to give the overall pollution premium,

$$F_Z(Z, L) - R = \frac{Z}{Z^K}\sum_{h\in\{Kant\}} \eta^h \frac{v'(X)}{u'(c_2^h)}\,\psi\, F_Z(Z, L)\,. \tag{2.25}$$

By initial inspection of equation 2.25, it is not clear how the inclusive Kantian pollution premium compares to the Pareto efficient pricing rule (eq. 2.11). In Appendix B4.1, we take the total differential of equation 2.25 to investigate how the total level of dirty investment changes as the proportion of non-Kantians in the economy increases. We find that the differential of aggregate dirty investment with respect to the proportion of non-Kantians is,

[4] In the numerator both terms are negative. In the denominator both terms are negative.

$$\frac{dZ}{d\delta}=\frac{\left[\frac{Z}{Z^k}\frac{N\eta\psi v}{u'\left(c_2^h\right)}\left[-1-(1-\delta)\frac{u''\left(c_2^{kp}\right)}{u'\left(c_2^{kp}\right)}\frac{\tilde{\beta}}{N}D+\frac{Z^n}{Z^k}\frac{(1-\delta)}{\delta}N\right]\right]}{\left[\frac{RF_{zz}}{F_zF_z}+\frac{Z}{Z^k}(1-\delta)N\,\eta\frac{v'(X)}{u'\left(c_2^h\right)}\psi\left[\frac{u''\left(c_2^{kp}\right)}{u'\left(c_2^{kp}\right)}\frac{\tilde{\beta}}{N}\,B+\frac{Z^n}{Z^k}\left(\frac{1}{Z}-F_{zz}A\right)\right]\right]}, \tag{2.26}$$

Where $A=\frac{\frac{\beta}{u''(c_2)}[-Nl_1F_z-wNl_2]}{\delta(Nl_1-u'^{-1}(\beta F_z)wNl_2)(1+u'^{-1}(\beta F_z)F_z)}>0.$

We find that the analytical solution has no definitive sign[5], suggesting that there are conflicting effects upon the overall level of dirty investment and that the relative size of these effects will depend upon the functional form of the utility and production functions and the calibration of parameter values.

The main difference between the inclusive Kantian and the exclusive Kantian equilibria is the multiplier of $\frac{Z}{Z^k}$ on the right-hand side of equation 2.25, which arises because inclusive Kantians consider all agents as co-movers in their Kantian hypothetical but can only change their own investment. This means that when the inclusive Kantian seeks to equalise the marginal cost from all pollution externalities with the marginal benefit from their own investment returns, they will likely have to invest more to cover the higher costs arising from non-Kantian dirty investment. Hence, due to this Kantian equilibrium effect, Kantian dirty investment is likely to rise as the number of non-Kantians increases within the economy. In contrast, the exclusive Kantian only seeks to equalise the marginal cost from pollution externalities arising from Kantian investment with the marginal benefit from their own investment.

However, when aggregate dirty investment rises, this pushes down the return on dirty assets, thus an increase in investment by Kantian agents may result in a reduction in investment by non-Kantian agents. Since it is not clear whether the increase in Kantian investment is greater than the subsequent decrease in non-Kantian investment, equation 2.26 has no definitive sign.

Overall, since non-Kantian dirty investment is expected to be higher than Kantian dirty investment, we expect the results from the exclusive Kantian equilibrium will carry over to the inclusive Kantian equilibrium, such that pollution will be greater than in the Pareto efficient equilibrium. However, we cannot analytically compare the inclusive Kantian equilibrium with the exclusive Kantian equilibrium.

[5] In the numerator the term outside the bracket is positive, whilst inside the bracket the first two terms are negative and the third is positive, with no clear dominance in scale. In the denominator the first term is negative, the second term has a positive term outside the bracket, and one negative and two positive terms inside the bracket, again with not clear dominance in scale.

Hypothesis 1: *In the Inclusive Kantian equilibrium, pollution is greater than in the Pareto efficient equilibrium.*

2.4 Simulations

To numerically investigate the relationship between the proportion of Kantians and the level of dirty investment and to compare the exclusive Kantian economy to the inclusive Kantian economy, we run a set of numerical simulations. Within these simulations, we assign functional forms to the utility and production functions which satisfy the assumptions within the model. The utility function is represented as a logarithm, such that $u(c) = \ln(c)$, whilst the production function is represented as the Cobb-Douglas function with $\alpha = 1/2$ for ease of exposition, such that $F(Z, L) = Z^{1/2}L^{1/2}$. We run some tests to investigate how sensitive our outcomes are to these functional forms, varying the utility function by introducing a Stone-Geary term for essential consumption in each period and varying the production function by investigating different capital shares.

Within Appendix B5 we derive expressions for k^k, z^k and z^n for the 8 different scenarios shown in table 2.1. In each scenario, we solve the three expressions simultaneously to estimate equilibrium values for Kantian and non-Kantian investment portfolios.

Table 2.1: Functional forms and type of Kantian within each simulation

Utility function	Production function	Exclusive Kantians	Inclusive Kantians
$U^h = \ln(c_1^h) + \beta\left(\ln(c_2^h) - \eta^h v(X)\right)$	$F(Z, L) = Z^{1/2}L^{1/2}$	Simulation 1 Eq.: B5.7, B5.9, B5.10	Simulation 2 Eq.: B5.7, B5.8, B5.9
$U^h = \ln(c_1^h) + \beta\left(\ln(c_2^h) - \eta^h v(X)\right)$	$F(Z, L) = Z^{1/3}L^{2/3}$	Simulation 3 Eq.: B5.11, B5.13, B5.14	Simulation 4 Eq.: B5.11, B5.12, B5.13
$U^h = \ln(c_1^h) + \beta\left(\ln(c_2^h - s) - \eta^h v(X)\right)$	$F(Z, L) = Z^{1/2}L^{1/2}$	Simulation 5 Eq.: B5.19, B5.21, B5.22	Simulation 6 Eq.: B5.19, B5.20, B5.21
$U^h = \ln(c_1^h - s) + \beta\left(\ln(c_2^h) - \eta^h v(X)\right)$	$F(Z, L) = Z^{1/2}L^{1/2}$	Simulation 7 Eq.: B5.27, B5.29, B5.30	Simulation 8 Eq.: B5.27, B5.28, B5.29
**To see equations refer to Appendix B5.*			

We use the software Maple to solve the three simultaneous equations within each simulation. We calibrate the parameters within all our models according to reasonable market estimates, adjusting to ensure that there are real solutions at the equilibria. The annual discount rate is set to 2%, such that over the life cycle model, assuming a worker is employed for 40 years, the intertemporal discount rate is $\beta = 0.98^{40} = 0.446$. We set $\theta = 0.181$ where $\theta = \eta v'(X)\psi\, N\frac{\beta}{1+\beta}$ and N is normalised to 1. This implies that $\eta v'(X)\psi = 0.3695$ reflects the damage from an additional unit of production, which is the multiplication of three terms: one reflecting the pollution arising from an additional unit of production, one reflecting the damage caused by this pollution, and one reflecting the disutility that arises from this damage. We set the constant return on clean assets to be, $R = 1.05$. We set the labour in each period to $l_1 = 0.225$ and $l_2 = 1$ where labour in the second period was chosen for simplicity of exposition, whilst labour in the first period was chosen to ensure stable solutions with positive optimal investments for $0 < \delta \leq 1$. Finally, wages in the first period are set to 1 and wages in the second period are determined endogenously.

There are three roots for each simulation. Only one of these roots satisfies the constraint that investment cannot be negative, and therefore we analyse this as the equilibrium solution. We repeat each simulation for different proportions of non-Kantians, $\delta = [0,1]$ at intervals of 0.1 to see how the equilibrium investment portfolios of Kantians and non-Kantians change as the proportion of non-Kantians within the economy increases.

2.4.1 Simulations 1 and 2: Exclusive vs Inclusive Kantians

Figure 2.1 demonstrates that simulations 1 and 2 confirm propositions 4 and 5, that the level of pollution in both the exclusive Kantian equilibrium and the inclusive Kantian equilibrium will be higher than the Pareto efficient level. The purple lines show that in both cases the average level of dirty investment rises as the proportion of non-Kantians in the economy increases, this pushes down the pollution premium on dirty assets and implies higher levels of pollution.

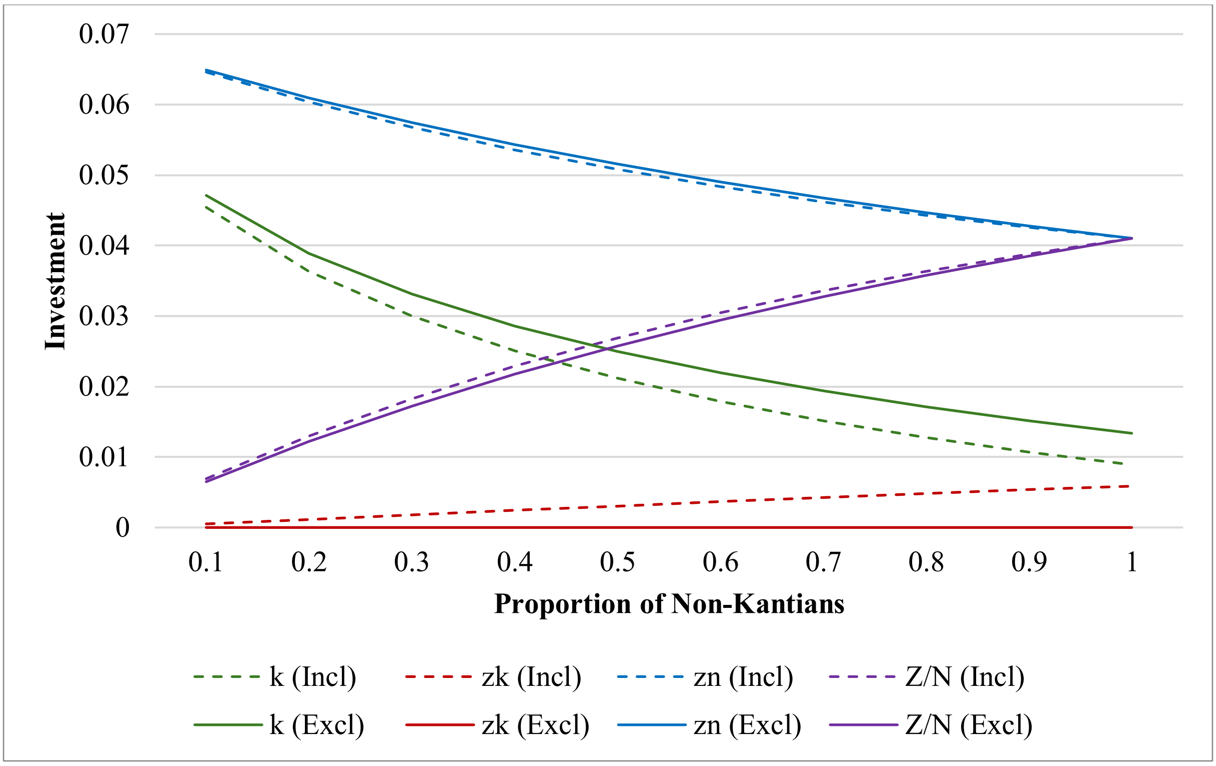


Figure 2.1: Graph to show the investment portfolio of Exclusive and Inclusive Kantians

** Exclusive Kantians in Simulation 1 (solid lines) and Inclusive Kantians in Simulation 2 (dashed lines). Where k is individual Kantian clean investment, zk is individual Kantian dirty investment, zn is individual non-Kantian dirty investment, and Z/N is average dirty investment.*

The blue lines show that as the proportion of non-Kantians increases, the individual investment of non-Kantians declines. This arises because at all values of $\delta \in [0,1]$ non-Kantians invest more than Kantians in the dirty firm. Therefore, as the number of non-Kantians increases, aggregate investment rises. However, as aggregate investment rises, the return on dirty assets is pushed down, thus reducing the incentive for non-Kantians to invest. Therefore, as aggregate dirty investment rises, individual non-Kantian investment falls. We can see that in the inclusive Kantian simulations, non-Kantian investment is slightly lower for $0 < \delta < 1$, due to the positive levels of Kantian dirty investment.

The red lines show that Kantian dirty investment differs significantly in the exclusive Kantian equilibria and the inclusive Kantian equilibria. In each of the exclusive Kantian equilibria, the solid line shows that the Kantian does not invest in the dirty firm. This aligns with the first-order condition for exclusive Kantian dirty investment in equation 2.21, where zero dirty investment will always be an available equilibrium since they only consider the damages generated by Kantian agents thus zero investment implies zero pollution damages and zero benefits from dirty investments. In contrast, the dashed red line demonstrates inclusive Kantians increase their dirty investment as the proportion of non-Kantians increases. This is because inclusive Kantians seek to equalise the marginal cost of all pollution damages with the marginal benefit arising from their own dirty investment. Thus, since the average dirty investment rises with the number of non-Kantians, pollution damages will also rise, resulting in a higher optimal level of Kantian dirty investment.

We can see that the increase in Kantian investment is greater than the subsequent reduction in non-Kantian investment, thus for all levels of $0 < \delta < 1$, the purple lines show that the average dirty investment in the inclusive Kantian equilibrium is slightly higher than in the exclusive Kantian equilibrium.

Finally, the green lines show that the optimal level of Kantian clean investment also responds to the proportion of non-Kantians in the economy. The solid lines show that exclusive Kantians, who invest solely in the clean firm, reduce their investment as the proportion of non-Kantians increases. This arises because as the level of dirty investment rises, the production of the dirty firm rises, pushing up labour income in period 2, $wl_2 = F - F_z Z = \frac{1}{2} Z^{\frac{1}{2}}$. Higher income in period 2 reduces the incentive to save in period 1, thus clean investment falls. The dashed lines show that inclusive Kantian clean investment reduces relatively more as the proportion of non-Kantians increases, this is because they are also substituting away from clean investment towards dirty investment.

2.4.2 Simulations 3 and 4: Exclusive and Inclusive Kantians with lower capital shares

To investigate how sensitive these results are to the functional form of the production function, we investigate how the simulation outcomes change when the capital share reduces to $\alpha = \frac{1}{3}$, such that the production function is $F(Z, L) = Z^{\frac{1}{3}} L^{\frac{2}{3}}$.

Figure 2.2 demonstrates that when the capital share declines the same general patterns arise in both the exclusive Kantian and inclusive Kantian equilibria, but the levels of all types of investment are lower[6]. The blue lines and the dashed red line show that investment in dirty assets declines for both non-Kantians and inclusive Kantians, resulting in lower average investment in the dirty firm as shown by the purple lines. This arises because when capital forms a smaller share in the production of the dirty firm, the marginal return to capital investment will fall, reducing the incentive to invest. Despite capital investment being lower, figure 2.3 shows that, given the same exogenous levels of labour, the overall production of the dirty firm will be higher. Therefore, when capital forms a smaller share in production, the investors' portfolios have a smaller influence on the production and subsequent pollution generated by firms.

[6] Figures B1 and B2 in appendix B6 demonstrate the difference between simulations 1 and 3, and simulations 2 and 4.

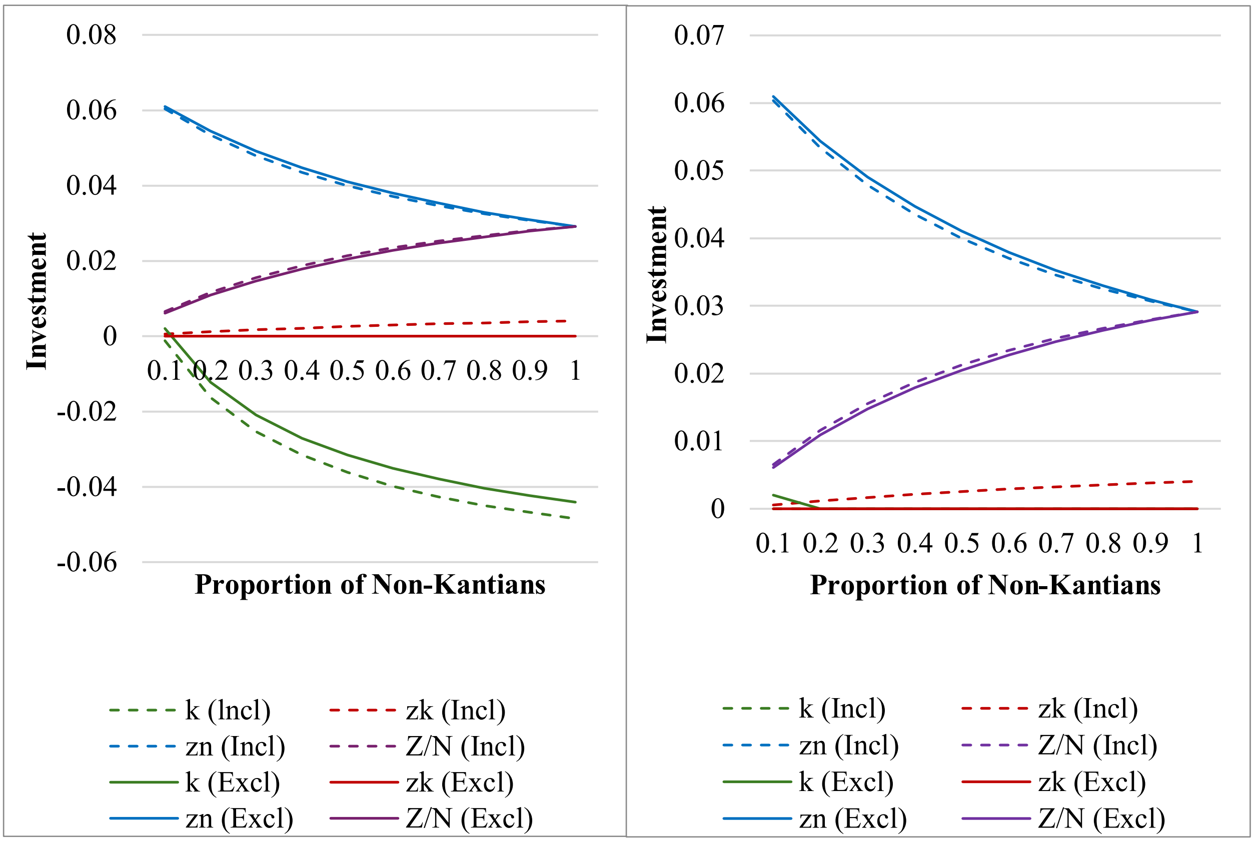


Figure 2.2: Graph to show the investment portfolio of Exclusive and Inclusive Kantians with lower capital share in production.

** Left graph allows for negative investment, right graph restricts optimisation to positive investment. Exclusive Kantians in Simulation 3 (solid lines) and Inclusive Kantians in Simulation 4 (dashed lines) when the capital share in the production function is reduced to 1/3, such that* $F(Z, L) = Z^{\frac{1}{3}}L^{\frac{2}{3}}$. *Where k is individual Kantian clean investment, zk is individual Kantian dirty investment, zn is individual non-Kantian dirty investment, and Z/N is average dirty investment.*

Figure 2.2 also demonstrates that Kantian clean investment is significantly lower when the capital share in production is lower. This is because a lower capital share implies a higher labour share, which results in a higher marginal return to labour in period 2, and thus lower incentive to invest in period 1 to fund period 2 consumption. With this calibration of parameters, the inclusive Kantian would want to invest a negative amount in the clean firm, thus would like to borrow from period 2 to fund consumption in period 1. Since this is not possible, the inclusive Kantian would be in a corner solution with $k = 0$ and positive dirty investments.

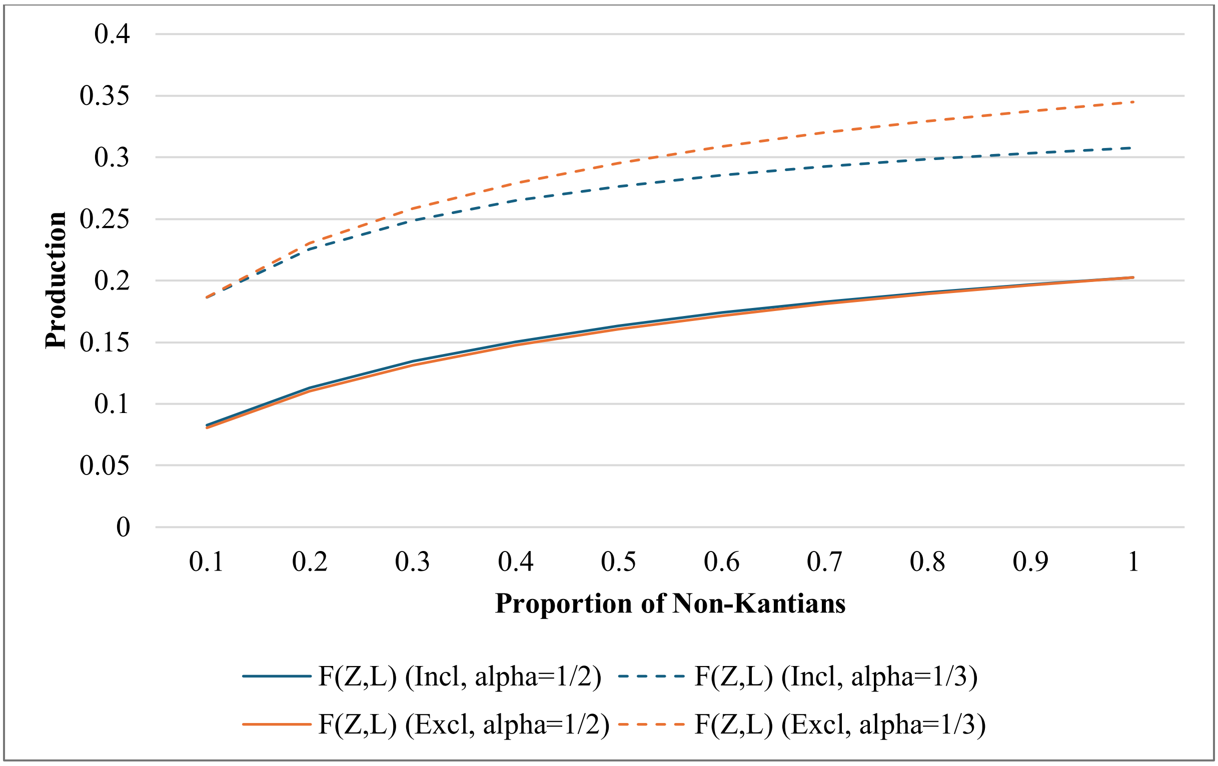


Figure 2.3: Graph to show the total production of the dirty firm in the Exclusive and Inclusive equilibria for each production function.

**Solid lines show the baseline model with alpha=1/2 such that* $F(Z, L) = Z^{\frac{1}{2}}L^{\frac{1}{2}}$*, dashed lines show the modified model with alpha=1/3 such that* $F(Z, L) = Z^{\frac{1}{3}}L^{\frac{2}{3}}$.

<u>2.4.3 Simulations 5,6,7, and 8: Exclusive and Inclusive Kantians with Stone-Geary Utility Terms</u>

The Stone Geary preference parameter, s, introduces a minimum consumption requirement. In simulations 5 and 6 we impose this requirement on period 2 consumption such that $U^h = u(c_1^h) + \beta[u(c_2^h - s) - \eta^h v(X)]$, whilst in simulations 7 and 8 we impose it on period 1 consumption, such that $U^h = u(c_1^h - s) + \beta[u(c_2^h) - \eta^h v(X)]$. A minimum consumption requirement implies that in the period in which the requirement is imposed, the individual will only gain utility from consumption above this minimum level, and that they would never choose a level of consumption below this level since utility would become negative or undefined in the case of logarithmic utility. Consequently, the consumption smoothing process is shifted. The investor would have an incentive to satisfy their minimum consumption requirement before optimising across periods, thus they would allocate more consumption to the period constrained by the Stone-Geary term. Within our simulations we apply a Stone Geary term that is 5% of the optimal period 2 consumption level for non-Kantians within a fully non-Kantian economy, thus we set $s = 0.0135$. We run the simulations with the baseline production function with $\alpha = \frac{1}{2}$.

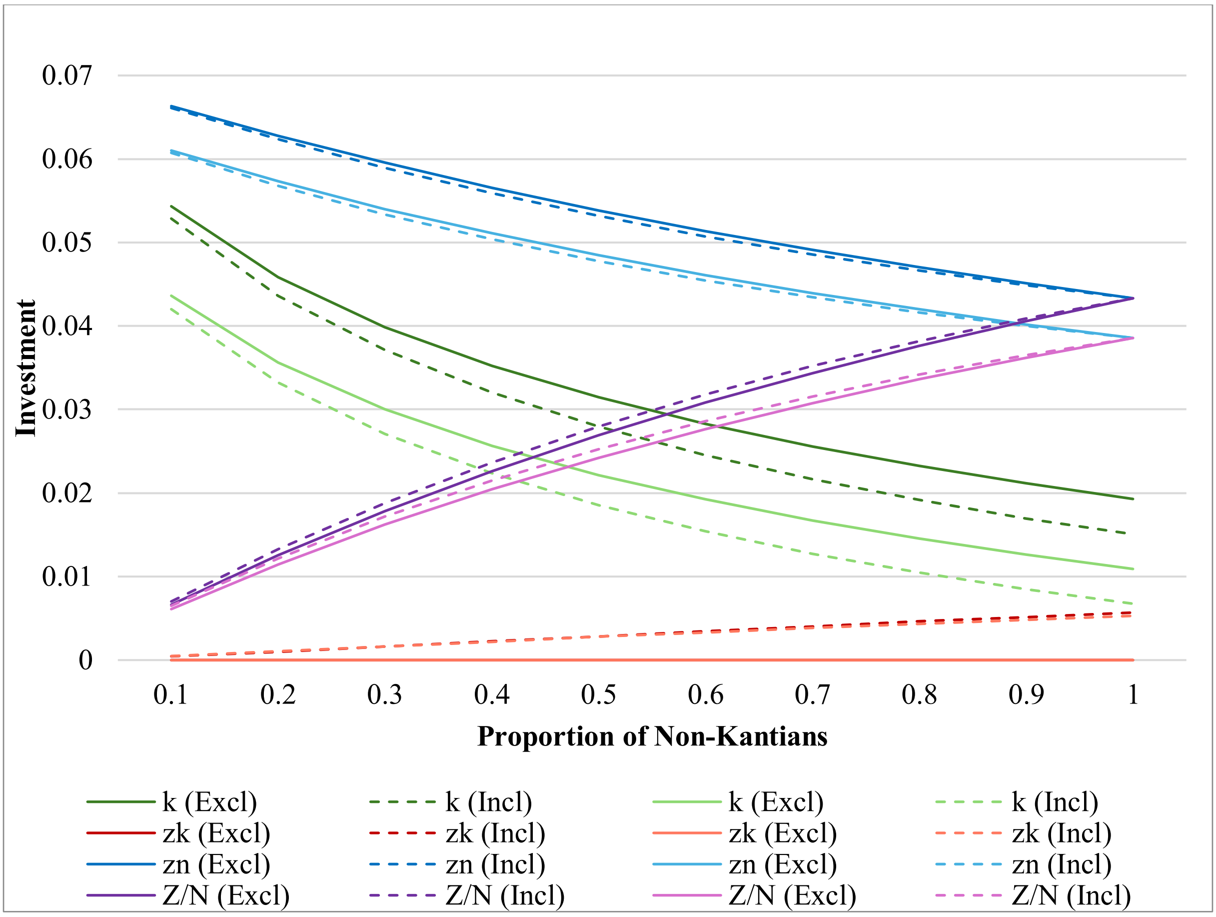


Figure 2.4: Graph to show the investment portfolio of Exclusive and Inclusive Kantians when Stone Geary term is introduced to utility function of investors.

**Exclusive Kantians in simulations 5 and 7 (solid lines) and Inclusive Kantians in simulations 6 and 8 (dashed lines). Dark colours show simulations 5 and 6 where the Stone Geary term is introduced in period 2, light colours show simulations 7 and 8 where the Stone Geary term is introduced in period 1. k is individual Kantian clean investment, zk is individual Kantian dirty investment, zn is individual non-Kantian dirty investment, and Z/N is average dirty investment.*

Figure 2.4 demonstrates that the general trends within Figure 2.1 are still evident when a Stone Geary term is applied. The dark lines in Figure 2.4 show that when the Stone-Geary term is introduced to period 2 utility, investors shift their consumption towards period 2 by increasing their investment. Non-Kantian agents have higher levels of dirty investment, and Kantian agents have higher levels of both clean and dirty investment. In contrast, when the Stone-Geary term is introduced to period 1 utility, investors shift their consumption towards period 1 by reducing their investment. Non-Kantian agents have lower levels of dirty investment, and Kantian agents have lower levels of both clean and dirty investment. The higher lines of simulation 5 and 6, and the lower lines of simulations 7 and 8 in Figure 2.4 sit above and below the baseline simulations 1 and 2 in Figure 2.1.

2.4.4 Simulations summary

Overall, our simulations demonstrate four key findings. Firstly, they confirm propositions 4 and 5, demonstrating that the presence of non-Kantians has a significant influence on the level of pollution within the economy, with the level of pollution increasing with the proportion of non-Kantians. Secondly, they demonstrate that the presence of non-Kantians significantly influences the investment portfolio of Kantian agents, and that this influence depends upon whether Kantians optimise in an exclusive or inclusive Kantian manner. Exclusive Kantians never invest in the dirty firm, but their clean investment declines with declining labour returns as the proportion of non-Kantians increase. Inclusive Kantians increasingly invest in the dirty firm as the proportion of non-Kantians rises, and their clean investment declines even further. Thirdly, they demonstrate that aggregate dirty investment and subsequent pollution is higher in the inclusive Kantian equilibrium than in the exclusive Kantian equilibrium when $0 < \delta < 1$. Finally, they demonstrate that within the assumptions of having a constant return to scale production function and a concave utility function, our results hold for different capital shares and Stone Geary consumption requirements.

2.5 Conclusion

We have presented a two-period model where heterogeneous households have a choice of clean and dirty investments. First, we derived a first-best, Pareto-efficient asset pricing rule, where the return on the dirty investment contains a pollution premium. We showed that when all investors are Kantian, the first-best asset pricing rule holds in equilibrium, and thus the externality is internalised. In this equilibrium, wealthier individuals will hold a larger share in the polluting firm. Furthermore, individuals with stronger preferences for the environment will hold a larger share in the polluting firm.

We next characterised the equilibria when only a fraction of the population is Kantian. We analytically derived the mechanisms underlying the partially Kantian equilibria and ran a series of simulations to investigate how investment portfolios changed as the proportion of non-Kantians increased and to compare the exclusive Kantian equilibria to the inclusive Kantian equilibria. If Kantians are exclusive, in the sense that they do what is morally right acknowledging that non-Kantians will not follow suit, then pollution will be greater than in the Kantian equilibrium. If Kantians are inclusive, in the sense that they do what is morally right according to what they believe that all agents, Kantian and non-Kantian, should do, then pollution will be even higher than in the exclusive Kantian economy when $0 < \delta < 1$. This is because in the inclusive Kantian optimum the marginal cost from all pollution damages is equal to the marginal benefit from a Kantian agents' own dirty investment, thus when aggregate non-Kantian investment in dirty assets rises, the inclusive Kantians also increase their dirty investment.

Understanding the potential mechanisms underlying socially responsible investment helps to design policy to further encourage and facilitate such investment patterns. Firstly, even in a fully Kantian economy, well-intentioned agents need to be informed about the externalities generated by firms and the cost of these externalities. Therefore, regulations mandating the provision of firms' environmental performance are key to allowing moral agents to make informed decisions. Furthermore, ensuring this information is digestible and simple is key to ensuring information is understood and has an influence on decision-making.

Furthermore, within a partially Kantian economy, we can see that as the number of Kantian agents rises and as the exclusivity of these agents rises, the economy comes closer to the Pareto optimum. This highlights the role for policy to emphasise the moral responsibility of individual investors and to empower them to make the changes that they want to see. However, it is also important for moral agents to be realistic about the scope of morality within the economy so that they can be more effective in promoting social welfare. Kantians are more effective in internalising externalities when they are focused on the impact that they can have as moral agents, rather than concerning themselves with the behaviour of non-moral agents.

Evidently, there is still an important role for market-based intervention. Whilst the pollution premium acts as an implicit tax upon dirty firms, it also serves to reward non-Kantian investors for investing in dirty assets. This could have the negative consequence of encouraging harmful behaviours, whilst also placing these harmful assets in the hands of less responsible people. On the other hand, an explicit tax would increase costs for firms without providing financial incentives for non-Kantians to increase their investments in dirty assets.

Our contribution is to derive the asset pricing rule, and the equilibrium pollution levels under (i) efficiency, (ii) full Kantianism, (iii) partial exclusive Kantianism, and (iv) partial inclusive Kantianism. We have investigated the role of wealth and environmental preferences for the individually optimal portfolio. We showed that the need for government intervention depends on the proportion of Kantians in the population and the inclusivity of their moral norms.

CHAPTER 3: Coal Legacies and Geothermal Futures: Choice Modelling Analysis of Household Preferences for Renewable Heating Systems.

Lucy Naga*, Jingyuan Di, Kalila Mackenzie, Laura Marsiliani, Thomas Renström, Riccardo Scarpa.

Abstract:

Heating contributed 23% of the UK's greenhouse gas emissions in 2021. To achieve the government's commitment to net zero by 2050, decarbonisation of heating systems is crucial. This requires mass adoption of renewable, low-carbon heating systems by households and business owners. Within this paper, we investigate how environmental attitudes and social identity influence household stated preferences for four renewable heating systems: geothermal district heating from mines, hydrogen boiler, solar electric boiler and air source heat pump. We focus specifically on preferences for geothermal district heating from mines in the North East of England where coal mining heritage has a significant influence on local social identity.

We conduct a stated preference discrete choice experiment and employ an integrated choice and latent variable (ICLV) analysis approach. We find that those with environmentally friendly attitudes have a higher marginal willingness to pay for systems with lower carbon dioxide (CO2) emissions. However, although those with energy-conscious attitudes are more sensitive to CO2 emissions, their heightened cost sensitivity means that they are not willing to pay more for such systems. Our predictions demonstrate that a carbon price will shift demand towards geothermal energy. The elasticity of demand is lower for environmentally friendly respondents and higher for energy-conscious respondents. We also find that those who identify more strongly with the region's coal mining heritage view the use of coal mines more positively and are more likely to choose geothermal heating from mines, they are also more sensitive to the job creation attribute, yet more cost-sensitive. Overall, this suggests that coal mining communities will have a positive attitude towards the introduction of geothermal district heating. However, due to the high levels of deprivation and subsequent high levels of cost sensitivity, when the time comes, most households would be compelled to choose the cheapest option.

JEL classification: D12, D91, Q41, Q58.

Keywords: Energy economics, Choice modelling, Heating systems, Identity, Environmental Preferences.

Acknowledgements: UKRI/EPSRC for funding the project, Durham Business School for funding the survey. GEMS research team for inciteful discussions, particularly Chima Anyadike-Danes for insight into the history and culture of the North East.

*Corresponding author: Lucy Naga, Department of Economics, Durham University Business School, Mill Hill Lane, Durham, DH1 3LB, United Kingdom. lucy.v.hyde@durham.ac.uk

Kalila Mackenzie, Department of Economics, Durham University Business School, Mill Hill Lane, Durham, DH1 3LB, United Kingdom. kalila.h.mackenzie@durham.ac.uk

Laura Marsiliani, Department of Economics, Durham University Business School, Mill Hill Lane, Durham, DH1 3LB, United Kingdom. laura.marsiliani@durham.ac.uk

Riccardo Scarpa, Department of Economics, Durham University Business School, Mill Hill Lane, Durham, DH1 3LB, United Kingdom. Riccardo.scarpa@durham.ac.uk

Thomas Renström, Department of Economics, Durham University Business School, Mill Hill Lane, Durham, DH1 3LB, United Kingdom. t.i.renstrom@durham.ac.uk

Jingyuan Di, Choice Modelling Centre, University of Leeds, Woodhouse, Leeds, LS2 9JT, United Kingdom. j.di@leeds.ac.uk

3.1 Introduction

The UK government is committed to achieving net zero greenhouse gas (GHG) emissions by 2050 (BEIS, 2021a). Meeting this commitment requires research and innovation into low-carbon technologies alongside widespread behavioural change. Heating generated 23% of the UK's GHG emissions in 2019 (BEIS, 2021b), with household heating alone contributing 17%. Despite significant innovation in low-carbon heating systems and recent policy efforts to encourage adoption, households' transition away from fossil fuel heating sources has been slow. 78% of the UK homes are still heated by natural gas boilers (BEIS, 2021b). The government's Heat and Building Strategy (BEIS, 2021a) sets out its policy approach and plan to transition to low-carbon, renewable heating systems, including the phase-out of natural gas boiler installation beyond 2035. The report recognises the multi-faceted challenge of the transition but also emphasises the opportunities for improved welfare, growth, and levelling up.

Several low-carbon technologies are available in the market. A key technology being encouraged by the government as a 'no-regret' action (BEIS, 2021a) is the hydronic heat pump — including air source and ground source. Heat pumps extract heat from the air or the ground using technology similar to that found in a refrigerator or air conditioner. Warm air is pumped over a heat exchanger, causing a refrigerant liquid to evaporate and pass through a compressor which increases the pressure and raises the temperature. This heat is then transferred to the home or target space. Solar electric heat is another alternative, whereby photovoltaic (PV) cells absorb sunlight and create electricity to power an electric boiler. Research and development into alternative low-carbon heating systems is ongoing, with several viable alternatives not widely available in UK markets. Hydrogen-fuelled boilers are one alternative, whereby hydrogen is extracted by electrolysis within power plants and then burnt for energy within household boilers. Hydrogen is a low-carbon fuel and does not release carbon dioxide when burnt. However, the overall emissions depend upon how the hydrogen gas is generated. Geothermal district heating is another alternative, whereby deep ground sources such as mines are used as a source for geothermal heat which can be extracted via heat pump technology and then distributed within a district heat network.

It is unlikely that there is a one-size-fits-all solution (BEIS, 2018); subsequently, multiple technologies will be important on our path to net zero. Natural resources and existing infrastructure play a fundamental role in the viability and efficiency of the different heating sources. In this project, we are focusing on consumer preferences for heating systems within the North East of England. The North East has an abundance of disused coal mines, a remnant of its strong coal mining heritage. Over time, these mines have filled with water and this water has been heated by natural geothermal processes to 10-15 degrees Celsius (British Geological Society). Heat pump technology can boost this to temperatures of up to 40-50 degrees Celsius (Geological Society of London), hence providing a viable source of household heating. Geothermal district heating systems are set up as a renewable process. Warm water is extracted from a deep mine seam, and cooler water is returned to a shallower mine seam or the same seam some distance away. It then trickles through the rocks, heating up on its journey to the extraction point. There is also the potential to use these systems to store and recycle waste heat.

Demographically, the North East is one of the most deprived regions in the country, therefore many households may struggle to afford investments in low-carbon heating alternatives. A renewable energy project which draws on resources within the region, generates green jobs for residents, and offers a source of affordable and renewable energy appears to offer a win-win scenario for households. Within this paper, we investigate households' attitudes towards geothermal district heating, exploring their willingness to pay for different renewable heating systems and how their environmental preferences, energy-saving inclinations, and coal mining identity influence their sensitivity towards different heating system attributes.

We administer a discrete choice experiment through a survey of 915 households in the North East of England to investigate household willingness to pay for geothermal district heating, a solar electric boiler, a hydrogen boiler, and an air source heat pump. We investigate which heating system attributes influence household decisions by varying levels of investment cost, monthly cost, replacement period, CO2 emissions and job creation.

Alongside our choice experiment, we ask a series of attitudinal questions relating to environmental attitudes, energy behaviours and coal mining identity. We also collect information on respondents' socio-demographic characteristics as well as details relating to their house and current heating system. We match respondents' postcode areas to information about coal mine locations to obtain more detailed respondent-specific information about mining identity and the legacy of coal mining within the region. We first use data from the choice experiment and survey questions to conduct a baseline multi-nominal logit (MNL) model. We then investigate patterns of heterogeneity by introducing household characteristics into the MNL model, by estimating a mixed logit (MXL) model to incorporate a random continuous source of heterogeneity, and by estimating integrated choice and latent variable (ICLV) models to incorporate latent behavioural determinants. We finally focus on the role of environmental and energy attitudes and coal mining identity.

Our preliminary factor analysis reveals that indicators for pro-environmental attitudes and energy-saving attitudes load onto separate factors, leading us to investigate them as distinct latent variables. Within our ICLV model analysis, we find that respondents with stronger pro-environmental attitudes exhibit a higher sensitivity to CO2 emissions; when an MNL choice structure is applied, this translates to a higher willingness to pay for heating systems with lower CO2 emissions than the average willingness to pay in the sample. Yet, when an MXL choice structure is applied, whilst heightened sensitivity to CO2 emissions remains, cost sensitivity increases, suggesting that underlying random parameters that correlate to environmental attitudes are the drivers of heightened willingness to pay in the MNL model. In contrast, both ICLV models find that, whilst those who have stronger energy-saving attitudes are more sensitive to CO2 emissions, their heightened sensitivity to cost means they do not have a higher willingness to pay for heating systems with lower CO2 emissions. Our policy predictions demonstrate that when a carbon price is introduced, households would be expected to shift their demand to cleaner alternatives. Households with stronger pro-environmental attitudes have a less price elastic demand than average, whilst households with stronger energy-conscious attitudes have a more price elastic demand.

Additionally, we find that respondents with stronger coal mining identity are more likely to choose geothermal district heating over other renewable heating alternatives. Furthermore, coal mining identity is associated with a greater sensitivity to job creation. However, again, due to the heightened cost sensitivity of this segment, this does not translate into a higher willingness to pay for job creation. Within our policy predictions, coal mining identity does not significantly influence demand responsiveness.

The rest of the paper is constructed as follows. Section 3.2 is a literature review of each of the behavioural theories and the choice modelling methodology. Section 3.3 covers the methods employed within this paper, including the survey design, data collection and choice modelling specifications. Section 3.4 provides an overview of our data. Section 3.5 presents the analytical results. Section 3.6 presents our model predictions in the case of a carbon tax and a technology-specific subsidy. Section 3.7 concludes and highlights the key takeaways.

3.2 Literature

3.2.1 Behavioural Influences

Over the last several decades economists have enriched our conception of economic agents beyond the narrow, self-interested, independent homo-economicus by incorporating vital elements of our shared humanity such as our identity (Akerlof and Kranton, 2000), social context (Duflo, 2017), social norms (Elster, 1989; Nyborg, 2018), moral values (Laffont, 1975; Roemer 2010) and ways of life (Collier, 2016) into models of behaviour. Sen (1977) highlights how the homo-economicus was never conceived as a realistic depiction of humans, but rather it was intended as a simplification of an economic agent acting within a perfect market situation. However, the reality of pervasive market failures in the form of imperfect and asymmetric information, externalities, and interdependence between agents, means that community networks, informal social contracts, and moral rules play a significant role within economic scenarios. Thus, when seeking to understand decision-making within real-life scenarios, it is important to consider this enriched concept of economic agents.

3.2.1.1 Pro-environmental and Energy-saving Attitudes

Economic behaviour in the context of environmental externalities is particularly susceptible to agents' human qualities due to the prevalence of negative environmental externalities and coordination failures which require social structures and moral rules to resolve. Since economic agents are many and their individual actions have a negligible external effect on the environment, it would be rational for each to act as homo-economicus and disregard their effect on externalities and focus on maximising their individual welfare. However, social structures and moral rules sustained through laws and norms enable economic agents to coordinate and collectively reduce their impact on the environment. Social psychology frameworks such as the Behavioural Reasoning Theory (BRT, Westaby, 2005; Claudy *et al*., 2013), and the Value-Belief-Norm framework (VBN, Stern *et al.,* 1995, 1999) suggest that it is these social structures, values, and worldviews that determine individual pro-environmental attitudes and intentions and that attitudes and intentions are the most significant antecedent to behaviour (Westaby, 2005; Claudy *et al.,* 2013).

The ONS Opinions of Lifestyle Survey (OPN) (July 2024) found that 58% of adults in Great Britain expressed concern about the impact of climate change and Deloitte (2023) suggest that this concern and the pro-environmental attitudes associated with it are growing. This trend is likely driven by advancements in scientific research demonstrating the impact of human behaviour on the environment and climate, alongside increased access to reliable information and firsthand experiences of environmental impacts. Social psychology theories suggest that with a growth in environmental attitudes, we should observe more environmentally friendly behaviours, which should imply a greater willingness to pay for environmentally friendly alternatives than before. People will put their money where their values lie, perhaps due to a desire to feel a warm glow (Andreoni *et al.,* 1991) from contributing to the environment, or from doing the socially acceptable or morally right thing (Nyborg, 2018).

The New Ecological Paradigm (NEP) scale (Dunlap *et al.,* 2000) is the most widely used measure of an individual's environmental concern. The NEP is a validated psychometric scale, which captures the 'pro-ecological' worldview of respondents through 15 Likert-style survey statements concerning human impact on the environment, the balance of nature, and the responsibility of humans to look after the planet. Stern *et al.* (1995) incorporated the NEP into their behavioural framework as a general belief or worldview which is influenced by values and affects specific individual environmental beliefs and pro-environmental attitudes.

The impact of pro-environmental attitudes on behaviours concerning renewable energy systems, and the attendant willingness to pay (WTP), has been investigated with structured survey tools based on contingent valuation (Hansala *et al.,* 2008; Koto and Yiridoe, 2019) and choice experiment (Amador *et al.,* 2013; Cicia *et al.,* 2012; Petrovich *et al.,* 2019) methods. These studies often use psychometric measures, such as the NEP scale, to capture latent environmental attitudes. Studies investigating marginal WTP for higher shares of renewable energy generation in their supplier's energy mix find that environmental preferences have a positive impact on it (Amador *et al.,* 2013), whilst those investigating preferences for particular energy sources generally find stronger preferences for renewable energy sources among respondents who worry more about climate change and have stronger environmental preferences (Cicia *et al.,* 2012; Koto and Yiridoe, 2019; Hansala *et al.,* 2008).

In their study on microgeneration technologies, Scarpa and Willis (2010) highlight that whilst renewable energy generation is valued significantly by households, for the majority of households, this value was, at the time, insufficient to cover the higher capital costs of such technologies.

In general, pro-environmental attitudes are found to have a positive effect on behaviour which is insufficient to correct for the environmental externalities arising from this behaviour. This may be due to the attitudes not being strong enough, or there could be an attitude-behaviour gap limiting action (Westaby, 2005; Claudy *et al.,* 2013). Westaby (2005) suggests that even when individuals have strong attitudes toward a particular behaviour, reasons against the action may still be a barrier to agency. Thus, it is likely that despite having environmentally friendly attitudes, the extent to which this influences willingness to pay will be limited by financial barriers, practical barriers regarding retrofitting, or other behavioural barriers, such as status quo bias.

Attitudes towards energy-saving also have a significant influence on energy behaviours. Statistica (2024) shows that household electricity consumption has been consistently declining over the last 20 years. Households used to consume over 100 terawatt-hours of electricity every year, with a height of 126 terawatt-hours in 2005, this gradually dropped to approximately 92 terawatt-hours in 2023. This substantial decline is likely to be due to improvements in energy efficiency and a rise in energy-saving behaviours. There are two key reasons why households may have become more proactive about energy-saving practices. Firstly, it may manifest their pro-environmental attitudes as they wish to reduce their carbon footprint by reducing energy consumption (Gadenne *et al.,* 2011; Udalov *et al.,* 2017). Secondly, it may be motivated by money-saving objectives, since lower energy consumption reduces energy bills (Aravena *et al.,* 2016). In the case of energy usage, the cost is not necessarily a barrier to sustainable behaviour, since reducing energy usage reduces both cost and emissions, this can confound emissions-reducing motives with cost-reducing motives, thereby complicating their respective identification.

Amador *et al.* (2013) used energy-saving actions as an explanatory variable in a mixed logit analysis of electricity supplier choice. They find that respondents who engage in more energy-saving behaviours have a higher willingness to pay for renewable energies. This suggests that environmental preferences are strongly related to energy-saving attitudes.

Deloitte (2023) found that during the recent cost-of-living crisis, energy-saving behaviours increased whilst other more expensive environmentally friendly behaviours, such as purchasing from environmentally friendly brands and switching to renewable energy sources, decreased. This suggests that growth in energy-saving behaviours is partly motivated by cost-saving incentives.

3.2.1.2 Coal Mining Identity

Within culturally significant contexts, the identity and cultural values attached to actions and their outcomes can influence the economic behaviour of humans. The coal mining heritage of the North East of England is likely to influence how residents feel about the repurposing of mines (Beynon and Hudson, 2021) and the persistent economic effects of coal mine closure is likely to influence residents' prioritisation of collective social benefits.

Social psychologists posit that the self or 'ego' is a fundamental driver of individual behaviour (Akerlof and Kranton, 2000; Brown, 1986; Turner *et al.,* 1979). Identity encompasses all aspects of the self; values, personal goals, personal narratives, preferences, physical attributes, habitual behaviour and personality traits (Gatersteben *et al.,* 2014; Pillsbury, 1934). Thus, it corresponds to the foundational stages of behavioural theories such as VBN and BRT. The self or 'ego' determines how an individual sees themselves and their place in the world. Identity is a stable characteristic shaped by an individual's experiences and their social environment and interactions. Therefore, an individual's identity has a significant influence on both the objective of their behaviour and the behaviour they choose to achieve that objective.

Akerlof and Kranton (2000, p.717) posit that the choice of identity ‘may be the most important “economic” decision people make’ due to the fundamental impact it has upon behaviour. They introduce identity payoffs into an economic model of behaviour, modelling identity to be closely related to social categories. Within their model, everyone is assigned to a social category and has a notion of others’ assignment. Each social category is associated with different ideal characteristics and prescribed behaviours. Identity payoffs depend on the social status of one’s assigned social category, the extent to which one’s given characteristics match the ideal and the extent to which one’s own actions and others’ actions correspond to prescribed behaviours.

Gatersteben *et al.* (2014) state that identity and values are stable factors that transcend specific situations. Alesina and Giuliano (2015) and Grosfeld *et al.* (2013) demonstrate that even when the initial stimulus which developed the identity and the attendant prescribed behaviours disappear, the inclination to conform to such prescriptions remains. However, the degree of persistence is likely to fade over time. Kranton (2019) suggests that social distinctions and norms, whilst fixed in the short run, may be selected in the medium run, and may be endogenous in the long run, changing according to individual actions and events.

This study focuses on the North East of England where the strong coal mining heritage has had a significant influence on local culture and individual identity. Within the ‘Shadow of the Mine’ Beynon and Hudson (2021) set out the history of the North East, chronicling the development and demise of the coal mining industry and how this influenced geographical patterns of settlement, social and political structures, and economic conditions within communities. The remote locations of mines led to the formation of many remote rural pit villages where mining was the dominant, if not unique, source of livelihood. There was a strong sense of comradery and community within these pit villages. Coal miners developed this comradery as they worked together in harsh and risky working conditions. The coal miners and their families developed this sense of community as they came together in trade union action to fight for workers’ rights and against the closure of the mines.

Coal mining peaked in the 1920s with 1.2 million workers employed within the industry. However, from the 1960s onwards coal mine closure accelerated due to the rise of international competition in coal markets and due to the rise in alternative fuel sources such as natural gas. Furthermore, smaller mines at the heart of pit villages were replaced by large, mechanised mines in new towns on the North East coast. Whilst the miners’ strike increased the sense of community and comradery as workers came together to fight for their jobs and fight for coal mines to remain open, this broke down when the strikes failed and mines closed. Large-scale mine closures resulted in widespread unemployment and high levels of deprivation. Many men failed to find jobs, and those who did were unsatisfied with the unskilled nature of these jobs. Communities look back on their coal mining heritage with nostalgia.

Beatty *et al.* (2019) report on the present-day economic and social conditions in former coalfields in England, Scotland, and Wales. They find persistent effects of coal mining, with the population tending to be older with fewer working-aged residents due to outmigration for work. They find residents have a 1-year lower life expectancy, a higher proportion of long-term health conditions, and a higher number of working-age adults claiming incapacity benefits than the national average, largely due to a legacy of poor health conditions from working in the mines. This report was used to justify continued support for coalfield regions, to compensate for mining-related illnesses and to renew efforts to level up these areas.

Coal mining heritage is likely to have a significant influence on the identity of households in the North East. Households are likely to have strong feelings about their history, the legacy of coal mining and the remaining mining infrastructure. Households' views on politics and economic opportunities are also likely to be influenced by the process of mine closure, with there being strong views on job opportunities and the levelling up agenda. According to Akerlof and Kranton's (2000) economic theory of identity, this will influence their behaviour as they seek to align with the prescribed behaviours of this identity.

3.2.2 Choice Modelling Methodology

3.2.2.1 Choice Modelling Origin

Choice modelling is widely used to analyse the decision-making process of economic agents, to quantify their marginal willingness to pay for various attributes of alternatives, predict market behaviour, and inform policy design. Choice modelling is grounded in the theory of random utility maximisation (RUM) (Marschak, 1960; McFadden, 1976, 1986), which posits that decision-makers select the alternative that maximises their expected utility based on the available options and their attributes. Utility is derived from specific attributes of alternatives (Lancaster, 1966), prompting individuals to weigh and trade-off these attributes and select the option most aligned with their preferences. As such, observed choices are a manifestation of underlying utility.

3.2.2.2 Multinomial Logit Choice Models

The multinomial logit (MNL) choice model was first introduced by McFadden (1974) and is a foundational tool in discrete choice analysis. Also referred to as the conditional logit model, it represents the choice probability of an alternative to be conditional on its attributes. The MNL remains highly popular due to its closed-form solution and ease of interpretation, often serving as a baseline model for comparison in discrete choice studies.

McFadden (1974) drew upon insights from Marschak's (1960) RUM framework and Luce's (1959) Independence of Irrelevant Alternatives (IIA) axiom. The RUM model represents the utility of alternative i for individual n, U_{ni}, as a combination of a deterministic component, V_{ni}, and a stochastic component, ε_{ni}.

$$U_{ni} = V_{ni} + \varepsilon_{ni}. \tag{3.1}$$

The deterministic component is modelled using Lancaster's (1966) approach to consumer theory, whereby utility is a function of the observed attributes of the alternative. This is commonly specified as a linear function of the parameter vector and forms the structural equation within the choice model.

$$V_{ni} = \beta' x_{ni}, \tag{3.2}$$

where, x_{ni}, is a $(K * 1)$ vector of observed explanatory variables, with K representing the number of explanatory variables, and β' is a vector of unknown taste parameters to be estimated.

Meanwhile, the stochastic component, ε_{ni}, is assumed to follow an independently identically distributed (iid) Extreme Value Type 1 distribution, with a density function of $f(\varepsilon_{ni}) = e^{-\varepsilon_{ni}} e^{-e^{-\varepsilon_{ni}}}$. This ensures consistency between the RUM model of behaviour and the IIA axiom. The IIA axiom states that the ratio of probabilities for two alternatives is the same in every choice set that contains the two alternatives. This simplifies the empirical collection of choice data by allowing for multinomial choice probabilities to be inferred from binomial choice experiments.

The measurement equation relates the observed choice to the unobserved, underlying utility through the assumption of utility maximisation,

$$y_{in} = \begin{cases} 1 & \text{if } U_{in} \geq U_{jn} \quad \forall j \in C_n \\ 0 & \text{otherwise.} \end{cases} \tag{3.3}$$

Where y_{in} is a choice indicator equal to one if individual n chooses alternative i and zero otherwise, and C_n is the choice set for individual n.

The iid Extreme Value Type 1 distribution of the stochastic term determines the formulation of the choice model as a logit model since the distribution of the difference between two iid Extreme Value Type 1 variables is logistic. The probability that an individual n chooses alternative i is the close-form logit choice probability,

$$P_{ni} = \frac{e^{\beta' x_{ni}}}{\sum_j e^{\beta' x_{nj}}}. \tag{3.4}$$

McFadden (1974) demonstrates that a sample log-likelihood function with these choice probabilities is globally concave for linear-in-parameters utility, facilitating maximum likelihood estimation. Assuming each decision maker's choice is independent of other decision-makers, the probability of each individual in the sample choosing the alternative they were observed to choose is given by the following sample log-likelihood function,

$$\mathrm{LL}(\beta) = \sum_{n=1}^{N} \sum_{i} y_{ni} \ln P_{ni}\,. \tag{3.5}$$

Where $y_{n,i} = 1$ if alternative i was chosen by n, and $y_{n,i} = 0$ if it was not, according to equation 3.3.

There are three potential limitations of the MNL model.

Firstly, whilst the multinomial logit model can be enriched to incorporate systematic taste variations, it cannot handle random taste variations. For example, the hypothesis that low-income households may place more importance on the purchase price of alternatives can be incorporated through the taste parameter on the purchase price, β_{price},

$$\beta_{n,\text{price}} = \frac{\hat{\beta}_{\text{price}}}{I_n}. \tag{3.6}$$

Where $\hat{\beta}_{\text{price}}$ represents a common taste parameter, I_n represents household income, and $\beta_{n,price}$ represents a taste parameter which accounts for the effect of income on sensitivity to price. However, taste variations arising purely randomly or as a result of unobserved factors cannot be estimated. In this case, the taste parameter would be enriched with a random element, μ_n,

$$\beta_{\text{n,price}} = \frac{\hat{\beta}_{\text{price}}}{I_n} + \mu_n, \tag{3.7}$$

which would result in a composite error term within the utility function,

$$\bar{\varepsilon}_{ni} = \varepsilon_{ni} + \mu_n x_{ni,\text{price}} \ , \tag{3.8}$$

where $x_{ni,price}$ is the price attribute, which is multiplied by the composite β_{price} from equation 3.6 within the utility function. This error term is no longer independently or identically distributed. It is not independently distributed because μ_n enters the utility for each alternative, thus $\bar{\varepsilon}_{n,i}$ is necessarily correlated over alternatives. It is not identically distributed since the variation in attribute levels across alternatives implies that $Var(\bar{\varepsilon}_{n,i})$ varies across alternatives. Thus, the MNL model can no longer provide unbiased estimates of parameters. Henceforth, either the source of taste variation should be explicitly measured and incorporated into the model, or a different model specification is advised.

A second potential limitation lies in the strong assumption of IIA. When correct, the IIA assumption delivers consistent estimation of model parameters. But when choice probabilities do not satisfy the IIA property, the resulting estimations will be inconsistent. Chipman (1960) and Debreu (1960) set out the red-bus-blue-bus problem to demonstrate how proportional substitution patterns are not always suitable given the different relations substitutability between alternatives. The IIA assumption implies that if an attribute of one alternative changes in a way that increases the probability of this alternative being chosen, then demand for all other alternatives will fall by the same proportion.

Finally, the MNL model requires unobserved factors to be independent over time (Train, 2009). This may cause issues in repeated choice situations where unobserved factors are likely to be correlated over time. If the source of this correlation is observable, such as state dependence or lagged response, this can be accommodated within the model. However, unobserved sources of correlation may cause estimates to be biased. Daly *et al.* (2012) explicitly account for the repeated nature of choice experiments, by modelling the probability of a sequence of choices rather than each choice independently. This means that the MNL model can be used in stated preference choice experiments.

3.2.2.3 Mixed Logit Choice Models

Mixed logit (MXL) choice models overcome the potential limitations of the MNL model by allowing for random taste variation, correlation in unobserved factors over time, and unrestricted substitution patterns. The first simple mixed logit models within the economics literature followed shortly after the MNL model (Boyd and Mellman, 1980; Cardell and Dunbar, 1980; Train *et al.,* 1987a; Ben-Akiva *et al.*, 1993), however the full potential of MXL models was only realised upon the advent of simulation (Bhat, 1998; Brownstone and Train, 1998; Erdem, 1996; Train, 1998, 1999; Bhat, 2000).

There are two distinct but formally equivalent formulations of mixed logit models, the random coefficients formulation and the error components formulation. The random coefficient formulation supposes that the taste parameters vary across the population according to some distribution, $f(\beta|\Theta)$, and it is the parameters Θ of this distribution that are to be estimated (usually mean and variance). The error components formulation supposes that the stochastic term can be decomposed into an iid Extreme Value Type 1 element, and an error component that may be correlated over alternatives, thus allowing for flexible substitution patterns.

In general, the MXL is formulated as a weighted average of the logit formula for a panel of *T* choices evaluated at different values of β, for each individual *n*, with the weights given by the mixing distribution, which is the density function, $f(\beta|\Theta)$,

$$P_{ni} = \int \prod_{t=1}^{t=T} \frac{\exp(\beta_n' x_{nit})}{\sum_{j=1}^{J} \exp(\beta_n' x_{njt})} f(\beta|\Theta)\ d\beta. \tag{3.9}$$

Within the standard MNL, the mixing distribution is degenerate of fixed parameters b, such that $f(\beta|\Theta) = 1$ for $\beta = b$, and $f(\beta|\Theta) = 0$ otherwise.

Within the latent class logit model for a panel of *T* choices by each respondent *n*, the mixing distribution is discrete, with β taking a finite set of distinct values, $b_1, \dots, b_M$ with membership probability s_m that the respondent *n* acquires the preference parameters $\beta = b_m$ of the latent class *m.* The unconditional probability of observing a panel of *T* choices, each of a given alternative is then,

$$P_{ni} = \sum_{m=1}^{M} s_m \left(\prod_{t=1}^{t=T} \frac{\exp(b_m' x_{nit})}{\sum_{j=1}^{J} \exp(b_m' x_{njt})} \right). \tag{3.10}$$

Within most applications which have been called mixed logit models, the mixing distribution is continuous and may be specified by the researcher. Most applications employ normal and log-normal distributions (Train, 1998; Revelt and Train, 1998; Ben-Akiva and Bolduc, 1996), with log-normal distributions being used when the coefficient is known to have the same sign for every decision maker (Train, 1998), such as a negative cost coefficient. When estimating the choice model, the parameters of the mixing distributions for the random preference parameters across respondents, Θ, are estimated, since the β_n's are random terms that are integrated out to obtain the unconditional choice probability of the sequence of choices observed in the single panel. In the case of $f(\beta|\Theta)$ being the normal distribution,

$$P_{ni} = \int \prod_{t=1}^{t=T} \frac{\exp(\beta_n' x_{nit})}{\sum_{j=1}^{J} \exp(\beta_n' x_{njt})} \; \phi(\beta|b, W) \; d\beta \tag{3.11}$$

the mean, b, and the variance-covariance matrix (or its Choleski decomposition), W, of the taste parameters are estimated, i.e., $\Theta = \{b, W\}$.

3.2.2.4 Integrated Choice Latent Variable Models

Integrated choice latent variable models (ICLV) build upon the base of an MNL or an MXL (or other choice models such as the Multinomial Probit (MNP) model) and incorporate latent variables such as attitudes, values, and perceptions. ICLV models were first introduced by McFadden (1986), who sought to build a prototype for incorporating statistical analysis of psychometric data into discrete choice modelling to explicitly model the cognitive mechanisms that govern behaviour. McFadden formulated a linear structural equations (LISREL) model (Jöreskog, 1978; Everitt, 1984) which has formed the foundation for ICLV models.

As shown in figure 3.1, the ICLV model can be decomposed into a latent variable model component and a choice model component which is much like the MNL or MXL above but with latent variables included within the utility specification. Each component has a set of measurement equations which elicit the latent variable (e.g., latent attitude in the latent variable component, latent utility in the choice model component) from how it is reflected in attitudinal indicators or the choice indicator. Structural equations relate the latent variables to observed variables such as the socio-demographic characteristics of the respondent, attributes of the alternatives, or features of the choice scenario.

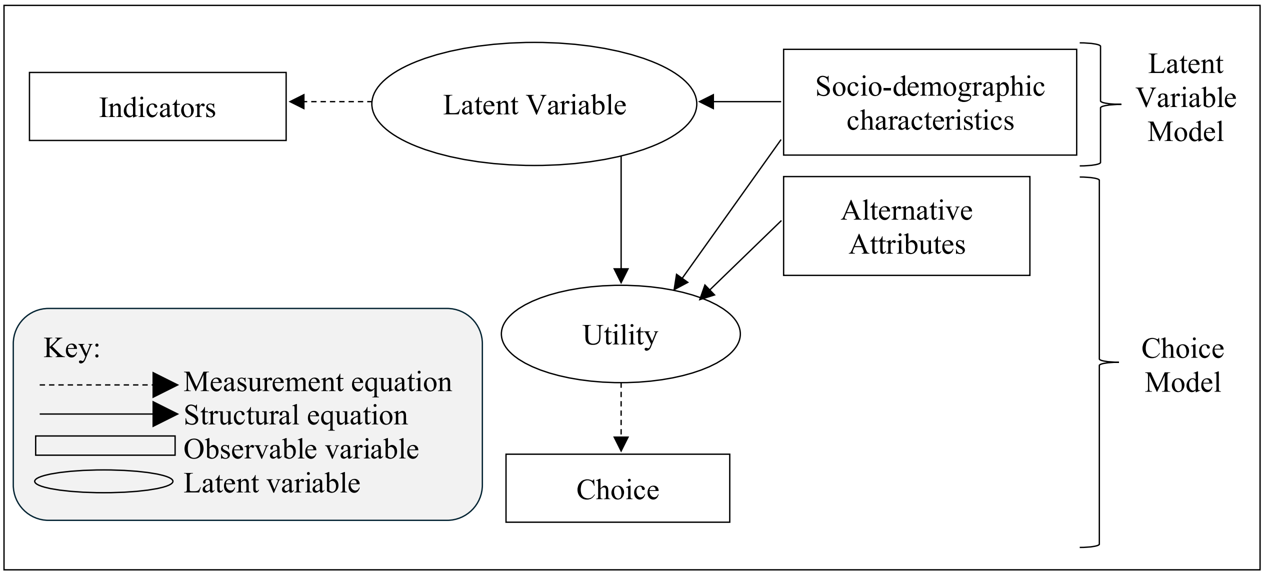


Figure 3.1: Schematic of Integrated Choice and Latent Variable (ICLV) model

Latent variables are unobservable and cannot be directly measured. Therefore, within the survey attitudinal questions are asked to indirectly obtain information about latent variables. The responses to attitudinal indicator questions are manifestations of individuals' latent attitudes (Abou-Zeid and Ben-Akiva, 2024). Values (Temme *et al.,* 2007), attitudes (Habib *et al.,* 2011), personality (Boyce *et al.,* 2019; Johassen *et al.,* 2006), social comparisons (Abou-Zeid and Ben-Akiva, 2011; Kamargianni *et al.,* 2014), identity (Facciolo *et al.,* 2020) and environmental attitudes (Facciolo *et al.,* 2020; Hoyos *et al.,* 2002; Johasson *et al.,* 2006) can be elicited through asking questions which reflect the respondents' position. Factor analysis can be employed to investigate which indicators are appropriate for each latent variable (Hoyos *et al.,* 2015; Mariel and Meyerhoff, 2016; Mariel *et al.,* 2018), and to test the validity of latent variables using factor loadings and Cronbach's Alpha.

The measurement equations within the latent variable model express each of the indicators in terms of a latent variable. It is common for indicator questions to be asked on discrete Likert scales. Daly *et al.* (2012) employ an ordered logit model structure to capture the ordinal nature of the indicators. For individual n and indicator $s \in (1,2, \dots S)$, the underlying unobserved continuous indicator, $I^*_{n,s}$, is expressed as a function of the relevant latent variable x^*_n,

$$I^*_{ns} = \eta_s x^*_n + \upsilon_{ns}, \tag{3.12}$$

where η_s shows the strength of this relationship between the indicator and the latent variable and υ_{ns} is a random variable.

Meanwhile, the observed discrete indicator, I_{ns}, reflects this continuous indicator with threshold parameters $\tau_1 < \tau_2 < \tau_3 < \tau_4$ determining which range of unobserved continuous responses matched each observed discrete indicator response.

$$I_{ns} = \begin{cases} 1 & \text{if} -\infty < I_{ns}^* \leq \tau_1 \\ 2 & \text{if}\, \tau_1 < I_{ns}^* \leq \tau_2 \\ 3 & \text{if}\, \tau_2 < I_{ns}^* \leq \tau_3 \\ 4 & \text{if}\, \tau_3 < I_{ns}^* \leq \tau_4 \\ 5 & \text{if}\, \tau_4 < I_{ns}^* \leq \infty \end{cases}, \tag{3.13}$$

The threshold parameters, $\tau_1, \tau_2, \tau_3, \tau_4$ are estimated along with the η_s parameters.

Structural equations within the latent variable model relate observed socio-demographic characteristics to latent variables,

$$x_n^* = \gamma\, x_n + \zeta_n. \tag{3.14}$$

Where x_n reflects a vector of observed variables and characteristics, and the matrix γ of parameters reflects how each observed variable relates to each of the latent variables. The random error term, ζ_n, accounts for random heterogeneity. Generally, structural equations in ICLV are weak (Anable, 2005; Vij and Walker, 2016), which implies the latent variable can provide explanatory power above and beyond observable variables and characteristics of the survey respondents.

The structural equation of the choice model may take a similar form to the MNL or MXL models above, with the addition of the latent variables as explanatory variables. As in equation 3.2,

$$V_{ni} = \beta' x_{ni}.$$

Where $\beta' = (\beta_1, \beta_2, \ldots, \beta_K)$ is a vector of coefficients on the observed $(K * 1)$ vector of alternative attributes, x_{ni}. The coefficient may be interacted with latent variables and/or observed variables such that for a given attribute k the coefficient depends on observable and latent characteristics of the individual,

$$\beta_{k,n} = \hat{\beta}_k + \lambda' x_n^* + \alpha' x_n. \tag{3.15}$$

Where λ' and α' are vectors of parameters to be estimated. Latent variables can be interacted with coefficients of attribute levels (Daly *et al.,* 2012; Hess and Beharry-Borg 2012) to investigate how sensitivities to particular attributes vary with latent attitudes, values or perceptions, or they can be incorporated directly into the utility specifications if the alternatives are labelled (Mariel *et al.,* 2015; Kassahun *et al.,* 2016) to investigate the influence on the alternative specific constants. As before, the measurement equation of the choice model is based on the random utility model.

To obtain efficient and consistent estimates of model parameters, all equations in the ICLV model are estimated simultaneously (Ben-Akiva *et al.,* 1999, 2002; Ashok *et al.,* 2002). Early choice models which sought to incorporate psychological constructs attempted to directly include indicators of latent variables into utility functions (Morey, 1981; Green, 1984; Harris and Keane, 1999), or sequentially estimated the latent variable model and then the choice model, where the latent variable was included as a deterministic variable (Anwar *et al.,* 2014; Bhat and Dubey, 2014). Two key issues arise with these approaches (Ben-Akiva *et al.,* 1999, 2002; Ashok *et al.,* 2002; Bolduc *et al.,* 2005), firstly measurement error arises when indicators or fitted latent variables are directly incorporated into the utility function since indicators are not a direct measure of the underlying latent variable, and fitted values contain error (Ashok *et al*., 2012; Ben-Akiva *et al.,* 2002). Secondly, endogeneity bias arises because responses to the attitudinal questions are correlated with unobserved factors that enter the error term of the choice model. The sequential approach can be made consistent by integrating the choice probability over the distribution of the latent variables (Ben-Akiva *et al.,* 2002). However, the simultaneous approach offers improvements in efficiency by using the information provided by both the choice and the indicators of the latent variables to provide the best fit.

To ensure that the model can be identified, it is necessary to normalise the scale of the measurement equation (eq. 3.12) for the latent variable. Daly *et al.* (2012) discuss two different normalisations that can be conducted. Firstly, the approach taken by Ben-Akiva *et al.* (1999), fixes the scale of the latent variable by constraining the parameters, η_s. The impact of each of the latent variables is normalised for one of the attitudinal indicators. In this case, the variance of the error term in the latent variable structural equation needs to be estimated. Secondly, in the approach taken by Bolduc *et al.* (2005), the variance of the error in the latent variable structural equation is normalised to 1, and the values of η_s are estimated. Daly *et al.* (2012) demonstrate that the two normalisations are equivalent.

Vij and Walker (2016) highlight that the ICLV model not only provides valuable behavioural insights into market decisions but can also improve the statistical performance of the choice model by correcting for bias from omitted variables and measurement errors and leading to lower variance of parameter estimates.

Whilst the behavioural insights and the identification of structural relationships between observable and latent variables may assist in practice and policy in ways not possible using reduced-form models, it is important to be aware of the limitations deriving policy implications from ICLV models. Chorus and Kroesen (2014) argue that ICLV models do not support the derivations of policies which aim to change behaviour through changing latent variables- for example, information campaigns aimed at changing attitudes to encourage particular behaviours. Firstly, they highlight that latent variables are usually endogenous to choices, which precludes inference of causality. Secondly, since most data on latent variables is cross-sectional, they highlight that no claims can be made concerning how changes in that latent variable at the individual level will change behaviour.

3.2.2.5 Choice Modelling and Energy Choices

Stated preference choice experiments provide a flexible tool to investigate preferences that determine energy behaviours, with hypothetical choices giving the analyst the opportunity to tune attribute levels and introduce alternatives that are not yet commercially available. Within energy economics, choice modelling has been used to investigate preferences for different energy mixes (Vecchiato and Tempesta, 2015; Borchers *et al.,* 2007; Zorić and Hrovatin, 2012), different renewable energy systems (Franceschinis *et al.,* 2016, 2017), and micro-generation energy systems (Scarpa and Willis, 2010; Willis *et al.,* 2011).

3.2.2.6 Choice Modelling, Identity, and Environmental Preferences

Stated preference choice experiments have been employed to investigate the influence of latent environmental attitudes and identity on different environmental and energy behaviours. Generally, hybrid choice models are employed, either in the form of integrated choice and latent variable models or in the form of latent class models (Meles *et al.,* 2022) where latent variables are used as explanatory variables in preference class membership equations.

Environmental attitudes are usually measured through Likert-style questions similar to the statements in the NEP scale. These responses are used as indicators within the latent variable model which is estimated simultaneously with the choice model to investigate the joint impact of latent environmental attitudes on indicator and choice task responses. In general, studies find that participants with stronger pro-environmental attitudes are more likely to select environmentally friendly alternatives and be willing to pay more for these alternatives (Daziano and Bolduc, 2013; Facciolo *et al.,* 2020; Taye *et al.,* 2018; Hoyos *et al.* 2015; Johansson *et al.,* 2006). However, in some cases such attitudes have an insignificant effect on behaviours (Sottile *et al.,* 2015), implying that an attitude-behaviour gap is present.

Similarly, studies have measured energy-saving attitudes through Likert-style questions relating to stated energy behaviours. Amador *et al.* (2013) find that respondents who carry out energy-saving actions in their homes have a higher willingness to pay for renewable energy.

Social identity has been measured through indicator questions asking how much an individual relates to particular identity traits. Environmental studies have found that place identity significantly influences individuals' preferences for the preservation of local landscapes. This is manifest in several forms, on the one hand, place identity increases willingness to pay for landscape preservation (Hoyos *et al.,* 2009; Facciolo *et al.,* 2020). On the other hand, it can decrease willingness to pay for renewable energy infrastructure which may negatively impact the local landscape (Strazzera *et al.,* 2012). Typically, local landscape features have spatially correlated WTPs (Campbell *et al,* 2009) and this spatial correlation fades with distance (Campbell *et al.,* 2008).

3.3 Methods

3.3.1 Survey

We designed a novel household survey which we first administered to a pilot sample of 100 households and then to a final sample of 915 households in the North East of England. We introduced the survey to respondents with a basic description of our Geothermal Energy from Mines and Solar Geothermal Heat (GEMS) project and a simple explanation of the survey structure and expected duration. We designed the survey with four sections: (1) Attitudinal questions, (2) Choice experiment, (3) Socio-demographic characteristics, (4) Heating and Housing characteristics. See Appendix C1 for the survey.

3.3.1.1 Attitudinal questions

Attitudinal questions were designed to capture environmental preferences, energy preferences, energy literacy, the strength of environmental social norms, the strength of coal mining identity, and attitudes towards energy system governance and energy policy. Within this paper, we are focusing on the influence of environmental and energy attitudes on willingness to pay for lower CO2 emissions reductions and the influence of coal mining identities on alternative specific constants and sensitivity to energy system attributes, particularly job creation. To elicit environmental and energy attitudes, we asked questions about the respondents' behaviours and beliefs, such as whether they are concerned about environmental damages caused by human activities and whether they adjust their thermostats to reduce their energy usage. To elicit the strength of coal mining identity, we ask respondents how strongly they identify with the 'proud mining heritage' of the North East and whether using mines for heating honours this history. Appendix C1 contains the attitudinal questions.

3.3.1.2 Choice experiment

Our choice experiment was framed within a hypothetical market scenario where the respondent was asked to suppose that they were selecting a new heating system for their new residential accommodation[1]. In light of the government's ambition to ban the installation of gas boilers by 2035 (BEIS, 2021a), four renewable heating alternatives were offered: geothermal district heating, hydrogen boiler, solar electric boiler, and air source heat pump. A basic description of each of these technologies was provided with demonstrative diagrams (as shown in Appendix C1).

Within the choice cards, the alternatives were portrayed based on five attributes: investment cost (cost of installation and connection to pipelines/grid of the heating system, GBP), monthly cost (monthly cost of the heating system for usage, maintenance, and repair costs, and fuel costs where relevant, GBP), replacement period (time from installation to dismantling/ end-of-life of the heating system, years), CO2 emissions (quantity of carbon dioxide equivalent emissions the heating system creates throughout its lifecycle; in production, usage and disposal, kg per year), job creation (number of full-time equivalent jobs created by the heating system when 1000 households adopt the heating system).[2] [3] Table 3.1 shows the attribute levels calibrated on the available market data and engineering literature (see Appendix C2 for more details on attribute level setting).

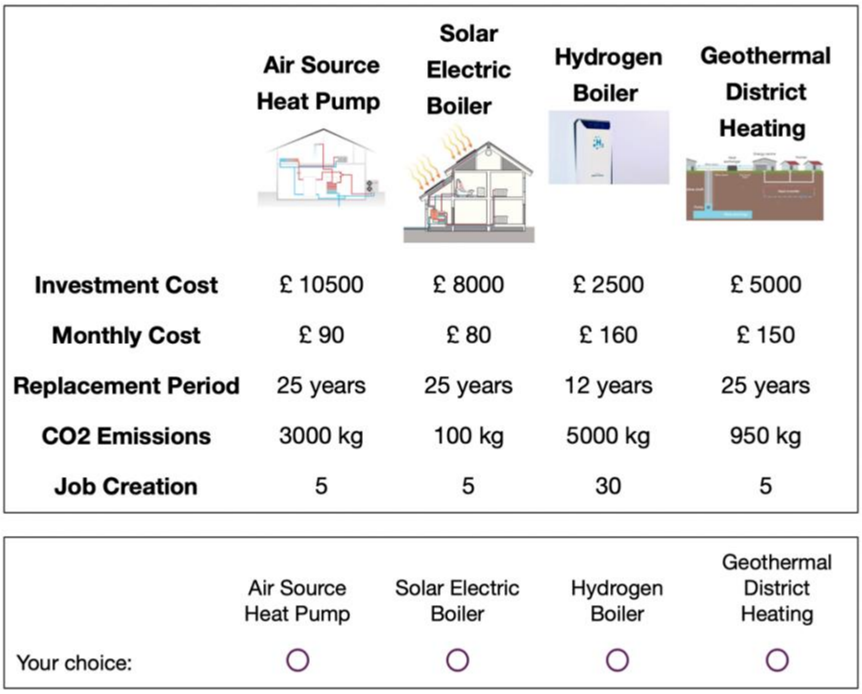
[1] We chose to focus on new heating systems for a new house for two reasons, firstly, to provide insight to choices for heating systems in new housing developments such as Seaham Garden Village in County Durham, secondly, to remove potential bias which could arise from house-specific retrofitting costs.
[2] We focus on gross job creation in new renewable energy industries. However, our results should be interpreted with caution since transition away from fossil-fuel energy sources will also initiate job loss, thus resulting in lower net job creation.
[3] We chose to represent the upfront costs, recurring costs and duration as separate attributes rather than combining them into a net present value to facilitate investigation into how socio-demographic characteristics and behavioural variables influence preferences towards each cost component individually.

Table 3.1: Table of attribute level settings

	Geothermal District Heating	Hydrogen Boiler	Solar Electric Boiler	Air Source Heat Pump
Investment Cost	£3,000, £4,000, £5,000, £6,000	£1,500, £2,500, £3,500, £4,500	£8,000, £9,500, £11,000, £12,500	£6,000, £7,500, £9,000, £10,500
Monthly Cost	£20, £60, £100, £150	£60, £110, £160, £210	£80, £120, £160, £200	£90, £110, £130, £150
Replacement Period	16 years, 18 years, 20 years, 25 years	12 years, 13.5 years, 15 years, 20 years	20 years, 22.5 years, 25 years, 30 years	16 years, 18 years, 20 years, 25 years
CO2 emissions	100 kg, 250 kg, 600 kg, 950kg	100 kg, 1000 kg, 5000 kg, 11000 kg	100 kg, 650 kg, 1200 kg, 1800 kg	350 kg, 1150 kg, 2000 kg, 3000 kg
Job creation	5, 10, 20, 30	5, 10, 20, 30	5, 10, 20, 30	5, 10, 20, 30

We chose to present respondents with twelve choice tasks. Higher numbers of choice tasks are important when investigating individual heterogeneity (Train, 2009; Sarrias, 2020) and can increase the likelihood of learning true preferences as respondents proceed through the choice cards (Hess *et al.,* 2012). However, too many choice tasks may raise issues regarding respondent fatigue and/or boredom and inattention, which could lower the scale of the model by increasing error variance (Bradley and Daly, 1994; Scarpa *et al.,* 2011; Hess *et al.,* 2012). We tested in our test pilot survey that twelve choice cards were manageable for respondents (Mariel *et al.,* 2021). Given that the literature finds that the number of attributes does not affect response efficiency (Caussade *et al.,* 2005; Meyerhoff *et al.,* 2015), we included all five attributes of key policy interest.

We employed the Ngene choice modelling design software to optimise the design of our choice experiment based on the attribute level settings in table 3.1. We used an optimal orthogonal in the differences (OOD) design (Street *et al.,* 2001, 2005), using the D-error to maximise the information available. Initially, using no prior parameters, we generated 80 choice tasks which we split into 10 blocks of 8 for the test pilot survey. We surveyed 80 respondents in the Durham area, analysed the results using MNL and MXL methods, and used these to update our priors and thus improve the efficiency of our design (Sandor and Wedel, 2001; Ferrini and Scarpa, 2007; Scarpa and Rose, 2008; Mariel *et al.,* 2021). Subsequently, we generated 48 choice cards in 4 blocks of 12 which we used in the pilot of our full survey of 100 respondents in the Northeast. We updated our priors once more to generate the 4 sets of 12 choice cards used within our final survey with 915 respondents. An example of the choice tasks presented in the survey is shown in Figure 3.2.



	Air Source Heat Pump	Solar Electric Boiler	Hydrogen Boiler	Geothermal District Heating
Investment Cost	£ 10500	£ 8000	£ 2500	£ 5000
Monthly Cost	£ 90	£ 80	£ 160	£ 150
Replacement Period	25 years	25 years	12 years	25 years
CO2 Emissions	3000 kg	100 kg	5000 kg	950 kg
Job Creation	5	5	30	5

	Air Source Heat Pump	Solar Electric Boiler	Hydrogen Boiler	Geothermal District Heating
Your choice:	○	○	○	○

Figure 3.2: Example of Choice Task

3.3.1.3 Socio-demographic characteristics

We ask questions about the respondents' gender, age, income bracket, educational level, occupational status, occupation type, marital status, family size, vehicle ownership, first half of postcode and country of birth.

We use the first part of respondents' postcodes (the outward code which indicates the postcode area and district) to identify their location, which we then link to information about mine locations and dates of coal extraction as well as local income, employment, and rural/urban statistics.

3.3.1.4 Heating and housing characteristics

We ask questions about the respondents' living and accommodation situations, about the type of accommodation (terraced, detached, semi-detached, apartment or mobile/temporary structure), whether they own or rent, the number of rooms in the house, length of time living in accommodation, and expected length of time living in accommodation in future. We also ask questions concerning the respondents' heating system, their house's energy performance (Energy Efficiency rating), and their council tax band. This helped us to uncover the links between energy demand and energy system choices.

3.3.2 Choice Analysis

3.3.2.1 Multinomial Logit Model

We begin by estimating a baseline MNL model, starting by including only product attributes, and subsequently investigating the influence of respondent socio-demographic characteristics.

First MNL specification:

$$V_i = \mathrm{ASC}_i + \beta_{\mathrm{InvCost}}\mathrm{InvCost}_i + \beta_{\mathrm{MonCost}}\mathrm{MonCost}_i + \beta_{\mathrm{RepPer}}\mathrm{RepPer}_i + \beta_{\mathrm{CO2}}\mathrm{CO2}_i + \beta_{\mathrm{Job}}\mathrm{Job}_i\ , \quad (3.16)$$

Where V_i represents the utility derived from alternative i, $\mathrm{ASC_i}$ represents the alternative specific constant for alternative i, $\{\mathrm{InvCost}_i, \mathrm{MonCost}_i, \mathrm{RepPer}_i, \mathrm{CO2}_i, \mathrm{Job}_i\}$ represent the attribute levels of alternative i, and $\{\beta_{\mathrm{InvCost}}, \beta_{\mathrm{MonCost}}, \beta_{\mathrm{RepPer}}, \beta_{\mathrm{CO2}}, \beta_{\mathrm{Job}}\}$ represent the marginal utility of each attribute.

Second, we interact each of the taste parameters with key socio-demographic and accommodation characteristics such that utility now depends on individual-specific characteristics.

$$\begin{aligned} V_{ni} = \mathrm{ASC}_i &+ \beta_{\mathrm{InvCost,n}}\mathrm{InvCost}_i + \beta_{\mathrm{MonCost,n}}\mathrm{MonCost}_i + \beta_{\mathrm{RepPer,n}}\mathrm{RepPer}_i \\ &+ \beta_{\mathrm{CO2,n}}\mathrm{CO2}_i + \beta_{\mathrm{Job,n}}\mathrm{Job}_i\ , \end{aligned} \qquad (3.17)$$

For each attribute $k = \{\mathrm{InvCost}, \mathrm{MonCost}, \mathrm{RepPer}, \mathrm{CO2}, \mathrm{Job}\}$,[4]

$$\begin{aligned} \beta_{k,n} = \hat{\beta}_k &+ \alpha_{\mathrm{LowInc},k}\mathrm{LowInc}_n + \alpha_{\mathrm{OwnAccom},k}\mathrm{OwnAccom}_n + \alpha_{\mathrm{Time10},k}\mathrm{Time10}_n \\ &+ \alpha_{\mathrm{ExpTime10},k}\mathrm{ExpTime10}_n + \alpha_{\mathrm{Male},k}\mathrm{Male}_n + \alpha_{\mathrm{UniEduc},k}\mathrm{UniEduc}_n \\ &+ \alpha_{\mathrm{Unemp},k}\mathrm{Unemp}_n + \alpha_{\mathrm{Age35},k}\mathrm{Age35}_n + \alpha_{\mathrm{Age3555},k}\mathrm{Age3555}_n. \end{aligned} \qquad (3.18)$$

Of key interest is the influence of income levels, whether they own their home, how long they have lived there and how long they expect to live there, gender, education level, employment status, and age. We construct each of these as dummy variables. Income is measured according to a threshold, where the discrete variable '*LowInc*' identifies households with income below £30,000, i.e., households in the bottom half of the income distribution of our sample. Whether they own their home outright or with

[4] Where the attribute abbreviations relate to the investment cost, monthly cost, replacement period, CO2 emissions, and job creation, respectively.

a mortgage is indicated by the '*OwnAccom*' discrete variable, whether they have lived there for more than 10 years is indicated by '*Time10*', and whether they expect to live there for a further 10 years is indicated by '*ExpTime10*'. Gender is specified as a dummy variable with '*Male*' equal to one for males and zero for females. Education level is specified as a dummy variable, '*UniEduc*', according to whether or not the respondent graduated from university, with one identifying those that are university graduates and zero those that are not. Employment status is measured by '*Unemp*' which indicates whether the individual is unemployed. Age is measured according to three thresholds, those under the age of 35, '*Age35*', those between 35 and 55, '*Age3555*', and those above the age of 55, that form the baseline group.

3.3.2.2 Mixed Logit Model

We proceed by investigating the degree of heterogeneity not captured directly by socio-demographic characteristics (i.e. unobserved) by means of a mixed logit model. We assume that (the negative of) the cost coefficients, β_{InvCost} and β_{MonCost}, follow a log-normal distribution since we expect all respondents to gain disutility from cost increases. We assume the remaining attribute level coefficients follow normal distributions, allowing for both positive and negative preferences towards them.

We then include both deterministic and random heterogeneity in an MXL model with socio-demographics.

3.3.2.3 Integrated Choice and Latent Variable Model

To investigate the influence of environmental preferences and coal mining identity we employ separate ICLV choice models. The first step we take is to investigate the validity of our latent variables by running a factor analysis on all the attitudinal questions relating to the environment, energy usage, and coal mining identity. Table 3.2 shows the estimation results of our factor analysis. We learn that the indicators load onto three factors: environmental attitudes, energy attitudes, and coal mining identity. Environmental attitudes and energy attitudes both have factor loading of greater than 0.5 for all indicator questions and each has a Cronbach Alpha greater than 0.7. This implies that they are valid latent variables, which are strongly reflected in the attitudinal questions. Coal mining identity has lower factor loadings and a Cronbach alpha of 0.594. This implies that it is a weaker latent variable, but that there is some common reflection of coal mining identity in the attitudinal questions. We investigated whether the strength of the coal mining latent variable improved when we omitted some of the attitudinal indicators, however we found that the latent variable was strongest when all three attitudinal indicators were included.

Table 3.2: Estimation of Factor analysis

Indicator	Indicator Descriptor	**Factor 1:** Environmental Attitudes	**Factor 2:** Energy Attitudes	**Factor 3:** Coal mining identity	**Communality**
Conc_env	'I am concerned about damage to the natural environment caused by human activities'	0.792			0.363
Change_life	'I make changes to my lifestyle to protect the environment'	0.638			0.514
Should_change	'I believe that people in the UK should make changes to their lifestyles to protect the environment'	0.727			0.429
Adj_therm_know	'I know how to adjust the thermostat/heating to reduce my energy usage'		0.713		0.484
Adj_therm_have	'In the past winter, I have adjusted my thermostat/ heating and/or used other ways to save energy'		0.596		0.581
Red_energy	'I know other ways to reduce my energy usage in the house'		0.794		0.345
Energy_dm	'I am involved in energy-related decisions in my household'		0.559		0.636
Iden_herit	'The North East of England claims to have a 'proud mining heritage'. I personally identify with this heritage'			0.555	0.687
Hon_his	'Using disused coal mines as a source of geothermal energy honours the history of coal mining'			0.559	0.595
Proj_imp	'Research projects like this one at Durham University are important for my community'			0.485	0.540
SS loadings		2.027	2.075	0.996	
Proportion Variance		0.184	0.189	0.091	
Cumulative Variance		0.373	0.189	0.463	
Cronbach's Alpha		0.785	0.776	0.594	
	Chi-square statistic: 583.52 on 25 degrees of freedom, p-value 3.31e-107				

3.3.2.3.1 ICLV: Environmental and Energy Attitudes

We first look at how environmental and energy preferences influence household willingness to pay for lower carbon dioxide emissions.

Within our latent variable model, we set out separate structural and measurement equations for each of the latent variables, as demonstrated in Figure 3.3. We specify structural equations (eq. 3.19 and 3.20) relating each of the environmental and energy attitudes to a set of observed respondent characteristics. We use the same respondent characteristics as in the structural equation for utility (equation 3.18), with the additional discrete variables of '$Renew_n$' which indicates whether the respondent currently has a renewable source of heating in their house.

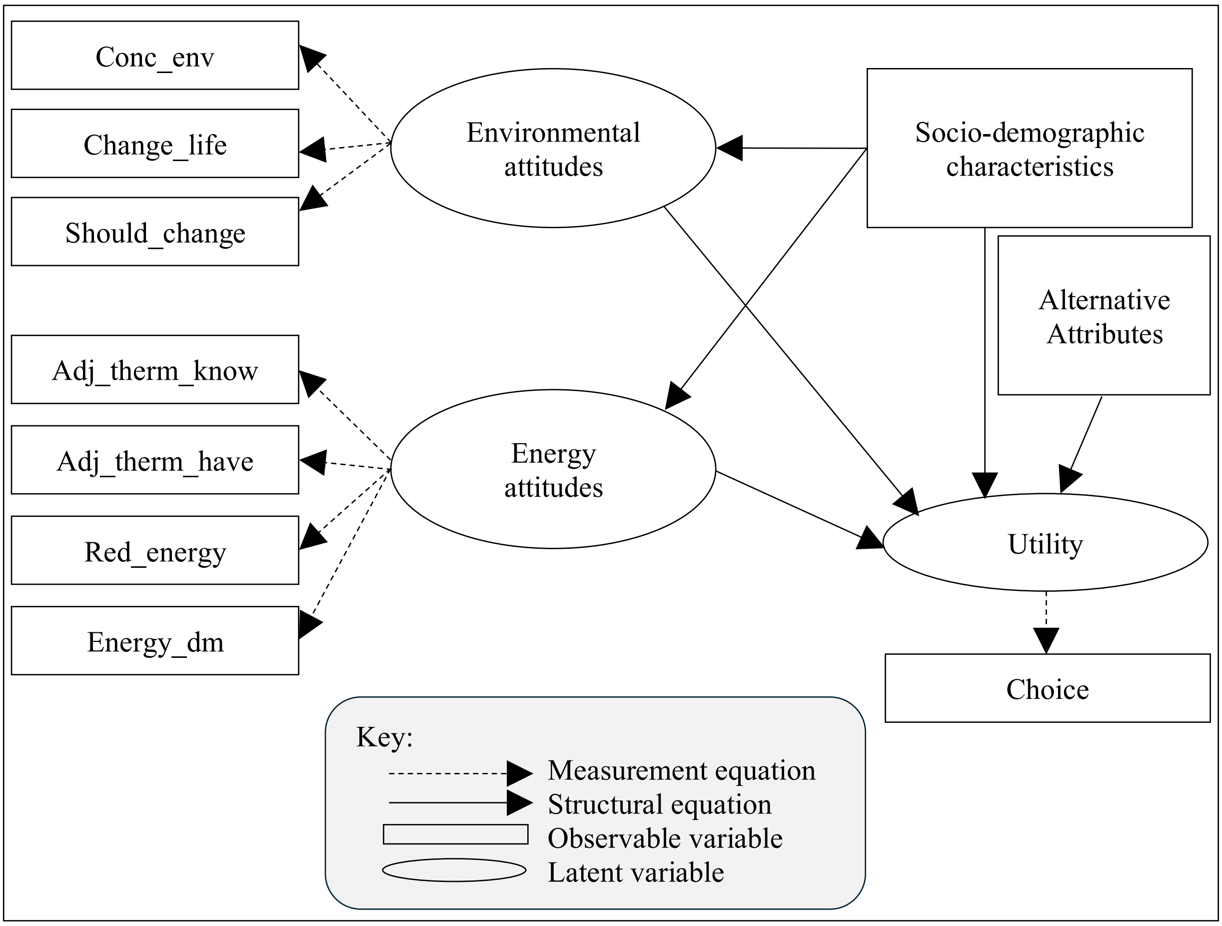


Figure 3.3: Schematic of Environmental and Energy Attitudes ICLV model

$$\begin{aligned}\mathrm{EnvAtt}_n^* = {} & \gamma_{\mathrm{LowInc}}^{\mathrm{env}}\mathrm{LowInc}_n + \gamma_{\mathrm{Male}}^{\mathrm{env}}\mathrm{Male}_n + \gamma_{\mathrm{UniEduc}}^{\mathrm{env}}\mathrm{UniEduc}_n + \gamma_{\mathrm{Unemp}}^{\mathrm{env}}\mathrm{Unemp}_n + \gamma_{\mathrm{Age35}}^{\mathrm{env}}\mathrm{Age35}_n \\ & + \gamma_{\mathrm{Age3555}}^{\mathrm{env}}\mathrm{Age3555}_n + \gamma_{\mathrm{OwnAccom}}^{\mathrm{env}}\mathrm{OwnAccom}_n + \gamma_{\mathrm{Renew}}^{\mathrm{env}}\mathrm{Renew}_n \\ & + \gamma_{\mathrm{Time10}}^{\mathrm{env}}\mathrm{Time10}_n + \gamma_{\mathrm{ExpTime10}}^{\mathrm{env}}\mathrm{ExpTime10}_n + \zeta_n^{\mathrm{env}}\end{aligned} \tag{3.19}$$

$$\mathrm{EneAtt}_{\mathrm{n}}^{*} = \gamma_{\mathrm{LowInc}}^{\mathrm{ene}}\mathrm{LowInc}_{n} + \gamma_{\mathrm{Male}}^{\mathrm{ene}}\mathrm{Male}_{n} + \gamma_{\mathrm{UniEduc}}^{\mathrm{ene}}\mathrm{UniEduc}_{n} + \gamma_{\mathrm{Unemp}}^{\mathrm{ene}}\mathrm{Unemp}_{n} + \gamma_{\mathrm{Age35}}^{\mathrm{ene}}\mathrm{Age35}_{n} + \gamma_{\mathrm{Age3555}}^{\mathrm{ene}}\mathrm{Age3555}_{n} + \gamma_{\mathrm{OwnAccom}}^{\mathrm{ene}}\mathrm{OwnAccom}_{n} + \gamma_{\mathrm{Renew}}^{\mathrm{ene}}\mathrm{Renew}_{n} + \gamma_{\mathrm{Time10}}^{\mathrm{ene}}\mathrm{Time10}_{n} + \gamma_{\mathrm{ExpTime10}}^{\mathrm{ene}}\mathrm{ExpTime10}_{n} + \zeta_{n}^{\mathrm{ene}} \tag{3.20}$$

The structural equations include a random component, $\zeta^{\mathrm{env}}, \zeta^{\mathrm{ene}}$, which is simulated using 2000 Sobel-Faure-Tezuka draws. We repeated simulations with 100, 500, 1000, and 2000 Sobel-Faure-Tezuka draws and found that the coefficients and standard errors were stable.

The measurement equations relate the environmental attitude latent variable to the three ordinal indicators that are loaded onto it in the factor analysis, and the energy attitude latent variable to the four ordinal indicators that are loaded onto it. We employ the order logit structure as in equations 3.12 and 3.13. For example, for the '*conc_env'*('I am concerned about damage to the natural environment caused by human activities') indicator, which signals ordinal strength of environmental attitudes, '$concEnv_{ns}^{*}$' is the unobserved continuous feeling that respondents would have toward the question, whilst '$concEnv_{ns}$' is the observed discrete response dictated by the Likert style questions, and '$EnvAtt_{n}^{*}$' is the unobserved latent attitude which is manifested within individuals' responses.

$$\mathrm{concEnv}_{n}^{*} = \eta^{concEnv}\mathrm{EnvAtt}_{n}^{*} + \upsilon_{n} \tag{3.21}$$

$$\mathrm{concEnv}_{n,s} = \begin{cases} 1 & \text{if} -\infty < \mathrm{concEnv}_{n.s}^{*} \leq \tau_{1}^{\mathrm{concEnv}} \\ 2 & \text{if}\ \tau_{1}^{\mathrm{concEnv}} < \mathrm{concEnv}_{n.s}^{*} \leq \tau_{2}^{\mathrm{concEnv}} \\ 3 & \text{if}\ \tau_{2}^{\mathrm{concEnv}} < \mathrm{concEnv}_{n,s}^{*} \leq \tau_{3}^{\mathrm{concEnv}} \\ 4 & \text{if}\ \tau_{3}^{\mathrm{concEnv}} < \mathrm{concEnv}_{n,s}^{*} \leq \tau_{4}^{\mathrm{concEnv}} \\ 5 & \text{if}\ \tau_{4}^{\mathrm{concEnv}} < \mathrm{concEnv}_{n,s}^{*} \leq \infty \end{cases}, \tag{3.22}$$

Within our choice model, we investigate the influence of environmental and energy attitudes on the alternative specific constants and the sensitivity to all K different product attributes.

$$V_{ni} = \mathrm{ASC}_{in} + \beta_{\mathrm{InvCost,n}}\mathrm{InvCost}_{i} + \beta_{\mathrm{MonCost,n}}\mathrm{MonCost}_{i} + \beta_{\mathrm{RepPer,n}}\mathrm{RepPer}_{i} + \beta_{\mathrm{CO2,n}}\mathrm{CO2}_{i} + \beta_{\mathrm{Job,n}}\mathrm{Job}_{i} \tag{3.23}$$

For each $i = \{\mathrm{Geo}, \mathrm{Hyd}, \mathrm{Sol}, \mathrm{Pum}\}$,

$$\mathrm{ASC}_{\mathrm{in}} = \widehat{\mathrm{ASC}}_{i} + \lambda_{\mathrm{env},i}\mathrm{EnvAtt}_{n}^{*} + \lambda_{\mathrm{ene},i}\mathrm{EneAtt}_{n}^{*}. \tag{3.24}$$

For each $k = \{\text{InvCost}, \text{MonCost}, \text{RepPer}, \text{CO2}, \text{Job}\}$,

$$\beta_{kn} = \hat{\beta}_k + \lambda_{\text{env},k}\text{EnvAtt}_n^* + \lambda_{\text{ene},k}\text{EneAtt}_n^*. \tag{3.25}$$

We estimate the latent variable model and the choice model simultaneously using a simulated maximum likelihood estimator with 2000 random Sobol-Faure-Tezuka draws. We run two versions of the ICLV model. The first has an MNL choice model, and the second has an MXL choice model with uncorrelated random parameters. In Appendix C5 we seek to investigate whether our behavioural hypotheses are robust to the introduction of correlated random parameters.

3.3.2.3.2 ICLV: Coal mining identity

We next investigate how coal mining identity influences which heating technology households are most likely to select, and whether it influences their willingness to pay for job creation.

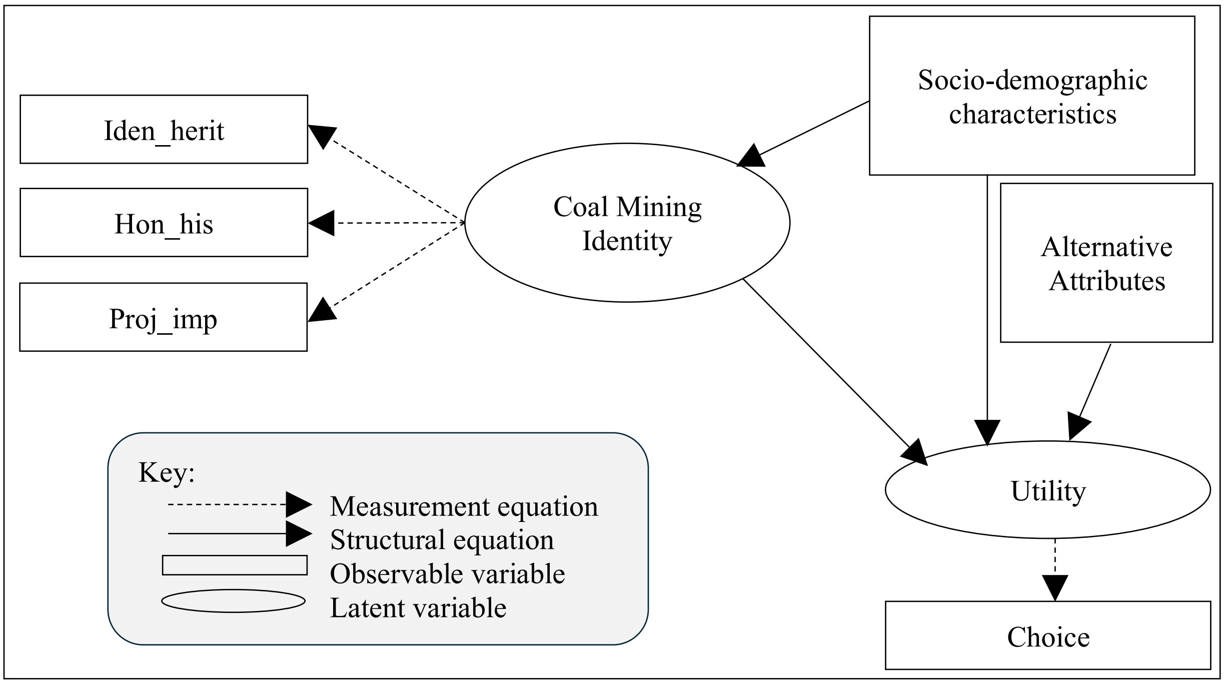


Figure 3.4: Schematic of Coal Mining Identity ICLV model

Within our latent variable mode, our structural equation relates the coal mining identity variable to respondent characteristics (as in equation 3.18) and includes a variable, '$NoMines_n$', which counts how many mines are located within the respondents' postcode area[5]. This was obtained by mapping the

[5] Data source: Northern Mine Research Society.

locations of mines and matching them to postcode locations on the mapping software ArcGIS, then merging this data to the postcode area data provided within the survey.

$$\begin{aligned}\text{Iden}_n^* = {} & \gamma_{\text{LowInc}}^{\text{iden}}\text{LowInc}_n + \gamma_{\text{Male}}^{\text{iden}}\text{Male}_n + \gamma_{\text{UniEd}}^{\text{iden}}\text{UniEduc}_n + \gamma_{\text{Unemp}}^{\text{iden}}\text{Unemp}_n + \gamma_{\text{Age35}}^{\text{iden}}\text{Age35}_n \\ & +\gamma_{\text{Age3555}}^{\text{iden}}\text{Age3555}_n + \gamma_{\text{OwnAccom}}^{\text{Iden}}\text{OwnAccom}_n + \gamma_{\text{Time10}}^{\text{iden}}\text{Time10}_n \\ & +\gamma_{\text{ExpTime10}}^{\text{iden}}\text{ExpTime10}_n + \gamma_{\text{NoMines}}^{\text{iden}}\text{NoMines}_n + \zeta_n^{\text{iden}} \end{aligned} \tag{3.26}$$

The measurement equations relate the coal mining identity latent variable to the three indicators that are loaded onto it in the factor analysis. Again, we employ an order logit structure as above.

Within our choice model, we include the latent variable directly into the utility function to investigate the influence of identity on the alternative specific constant for each of the alternatives and on the sensitivity to each of the different product attributes,

$$\begin{aligned}V_{n,i} = {} & \text{ASC}_{in} + \beta_{\text{InvCost,n}}\text{InvCost}_i + \beta_{\text{MonCost,n}}\text{MonCost}_i + \beta_{\text{RepPer,n}}\text{RepPer}_i \\ & +\beta_{\text{CO2}}\text{CO2}_i + \beta_{\text{Iob}}\text{Job}_i \end{aligned} \tag{3.27}$$

For each $i = \{\text{Geo}, \text{Hyd}, \text{Sol}, \text{Pum}\}$,

$$\text{ASC}_{\text{in}} = \widehat{\text{ASC}}_i + \lambda_{\text{Iden}}\text{Iden}_n^*. \tag{3.28}$$

For each $k = \{\text{InvCost}, \text{MonCost}, \text{RepPer}, \text{CO2}, \text{Job}\}$,

$$\beta_{kn} = \hat{\beta}_k + \lambda_{\text{Iden},k}\text{Iden}_n^*, \tag{3.29}$$

to ensure that there is no bias in the coefficient on the job creation attribute. Again, we estimate the latent variable model and the choice model simultaneously for the three different choice model specifications detailed above.

3.4 Data

3.4.1 Pilot Data

To optimise our choice card design, we collected two rounds of pilot data. In the first round, we collected data from 80 respondents in the Durham area. This pilot aimed to ascertain whether respondents understood the choice task[6] and to derive prior parameters to improve the efficiency of the choice card design (no additional questions beyond the choice experiment were included in the initial pilot). As described in the design section 3.3.1.2.1, we used a D-optimal design with no prior parameters to generate 80 combinations of alternatives which were grouped into 10 blocks of 8 choice cards. We randomly assigned respondents to a choice card block. Subsequently, we re-optimised our choice cards based on the prior parameters from our first pilot. Optimising the design of our choice cards ensures that we obtain the maximum amount of information from a limited number of choice tasks.

In the second round, we collected data through Qualtrics, a survey management company, from 100 respondents in the North East. We used 4 blocks of 12 choice cards and included the additional 3 sections of the survey. We were close to a block-balanced design with blocks 1 to 4 having 25, 26, 25, and 24 respondents respectively. The survey was structured with attitudinal questions first, then the choice experiment, and then the socio-demographic and housing characteristic questions. This pilot aimed to investigate if the other questions in our survey were clear, to check for any misunderstandings or errors, and to reoptimize the choice card design based on the target sample area of the North East. We found that sensitivity to CO2 emissions was lower than we had expected even from respondents who expressed higher levels of environmental concern. We added an additional explanation of CO2 emissions in the introduction to the choice cards, comparing CO2 emissions from heating to CO2 emissions from driving, which is more widely discussed and understood.

<u>3.4.2 Final Data</u>

Our final data was collected by Qualtrics with a sample size of 915 participants in the North East of England. We ensured that this sample was representative of the demographic structure by stratifying the sampling by gender and age group based on UK statistics provided by Qualtrics (as shown in Table 3.3).

Table 3.3: Sample stratification statistics

Age Group	Target Statistics	Sample
18-24	11.38%	11.26%
25-34	19.32%	19.78%
35-44	18.05%	18.14%
45-54	19.41%	19.45%
55-64	31.84%	16.72%
65 +		14.64%

[6] We discussed the choice cards with participants following completion to check for understanding and to ensure that there was not excessive cognitive strain.

Sex	Target Statistics	Sample
Male	49.5%	50.93%
Female	50.5%	49.07%

Each participant was faced with 12 choice tasks, with the 48 specifications thus blocked into four groups. Again, we were close to a block-balanced design with blocks 1 to 4 having 223, 236, 228 and 228 respondents respectively. The ordering of the alternatives in the choice tasks blocks was alternated in the final survey design. With 12 choices tasks and 915 participants, this generated 10,980 observations within our dataset.

3.5 Analysis[7]

3.5.1 Multinomial Logit Model Analysis

Column 1 of Table 3.4 shows the results from a simple MNL model with no socio-demographics. We have rescaled[8] the attribute levels such that parameter values are of a similar scale and not too close to zero, this improves the speed of the estimation procedure.

Table 3.4: Estimation of Multinomial Logit (Model 1) and Mixed Logit (Model 2)

	MNL (Model 1)	**MXL** (Model 2)
ASC_{geo}	0.892 (12.32)***	0.125 (1.47)
ASC_{hyd}	0.802 (9.40)***	-0.410 (3.63)***
ASC_{sol}	0.717 (9.13)***	0.712 (7.86)***
ASC_{pum}	0.000 (fixed)	0.000 (fixed)
$\beta_{InvCost}$	-0.956 (11.63)***	0.6705 (11.68)*** {-4.642}[1]
$\sigma_{InvCost}$		-1.315 (33.50)*** {9.995}[1]
$\beta_{MonCost}$	-0.758 (22.03)***	-0.286 (3.59)*** {-2.786}[1]
$\sigma_{MonCost}$		1.619 (20.62)*** {9.948}[1]
β_{RepPer}	0.323 (10.06)***	0.367 (8.62)***
σ_{RepPer}		0.875 (14.45)***
β_{CO2}	-0.775 (12.14)***	-2.542 (12.83)***

[7] All empirical analysis was conducted using the Apollo package in R (Hess and Palmer, 2019a, 2019b).

[8]Investment cost / 10,000; Monthly cost / 100; Replacement period / 10; CO2 / 10,000; Job / 100.

σ_{CO2}		3.724 (16.19)***
β_{Job}	0.689 (5.68)***	0.937 (5.83)***
σ_{Job}		1.460 (3.21)***
LL	-12,611.23	-10,489.41
*Absolute values of z-statistics in brackets, * 90% confidence, ** 95% confidence, *** 99% confidence correspond with 2-sided critical values 1.64, 1.96, 2.58 respectively.* *Where heating alternatives {geo, hyd, sol, pum} represent geothermal district heating, hydrogen boiler, solar electric boiler, and air source heat pump respectively.* [1]*Moments of the log-normal estimations in curly brackets, where* $\mu_\beta = -\exp\left(\mu_{log\,\beta} + \frac{\sigma^2_{log\,\beta}}{2}\right)$, *and* $\sigma_\beta = \mu_\beta * \sqrt{\exp(\sigma^2_{\log\beta}) - 1}$		

From the MNL model we can see geothermal district heating has the highest alternative specific constant, implying that all else equal, respondents seem to prefer this alternative to the others. We can also see that all the alternative attributes are statistically significant, implying that they all have a significant influence on the respondents' choice of heating system. To interpret these coefficients, we can use the MNL coefficient estimates to calculate a point estimate of the marginal willingness to pay for each attribute. We use the initial investment cost as the key cost attribute and calculate how much more respondents are willing to invest to obtain higher attribute levels by calculating the marginal rate of substitution between investment cost and each attribute.

Marginal willingness to pay for CO2 emission reduction is $\frac{\beta_{\text{CO2}}}{\beta_{\text{InvCost}}} = \frac{0.775}{0.956} * 100 = £81.07$ per 100 kg lower CO2 emissions per year. Assuming an average replacement period of 20 years, this would accumulate to 2 tonnes of CO2 emissions over the lifetime of the heating system, implying a carbon price of £40.54 per tonne of CO2 if we ignore the effects of time discounting. Alternatively, if we were to apply a discount factor of 2% per year, this would accumulate to $\frac{£81.07*0.98^{20}}{2}$= £27.27 per tonne of CO2. These are both less than half of the UK 2023 carbon price of £83.05 (UK ETS Authority, 2023), implying that whilst households are willing to pay for lower CO2 emissions, this would not cover the full cost of the externality.

Willingness to pay for job creation is $\frac{\beta_{\text{Job}}}{\beta_{\text{InvCost}}} = \frac{\frac{0.689}{100}}{\frac{0.956}{10{,}000}} = \frac{0.00689}{0.0000956} = £72.07$ per additional job created when 1000 households adopt the technology. If 1000 households were willing to pay this per job, this would accumulate to £72,098. We can compare this to the cost of job creation calculated by the IFS

(IFS, Spring Budget 2023) of £70,000. This implies that the collective willingness to pay for job creation is close to the market cost of job creation.

Willingness to pay for one additional year of life of the heating system is $\frac{\beta_{\text{RepPer}}}{\beta_{\text{InvCost}}} = \frac{\frac{0.323}{10}}{\frac{0.956}{10{,}000}} = \frac{0.0323}{0.0000956} =$ £338.04. Willingness to pay for £1 lower monthly bill is only $\frac{\beta_{\text{MonCost}}}{\beta_{\text{InvCost}}} = \frac{\frac{0.758}{100}}{\frac{0.956}{10{,}000}} = \frac{0.00758}{0.0000956} =$ £79.29. However, over 20 years, if the household saved £1 in real terms (no discounting the nominal value) every month for 20 years, they would save £240 in monthly bills. If this £1 were discounted at a monthly discount rate of $\frac{0.02}{12}$, then this would accumulate to a present discounted value of £229[9]. If this £1 were accumulated annually a discounted at an annual rate of 0.02, then this would accumulate to a present discounted value of £199[10]. The difference between a willingness to pay of £79.29 and the actual cost savings demonstrates the cognitive bias of temporal discounting, with respondents reluctant to pay higher costs now, despite greater cost savings in the future.

3.5.2 Mixed Logit Model Analysis

To investigate the degree of preference heterogeneity across respondents we estimate a panel mixed logit model, where the preference parameters on the product attributes are assumed to follow a continuous distribution, rather than being a single, discrete vector of preference coefficients applicable to all respondents. We assume that the parameters on the price attributes are distributed across respondents with a log-normal distribution based on the theoretical expectation of a strictly negative price elasticity of demand. We assume that the parameters on the other product attributes are distributed normally since both positive and negative sensibilities are conceivable. We estimate the maximum of the simulated log-likelihood function with 2000 random Sobel-Faure-Tezuka draws, which is high enough to reduce the simulation variance of the estimates.

Column 2 in Table 3.4 shows the results of the MXL model. We can see that there is a significant degree of heterogeneity, with all random parameters having a statistically significant standard deviation estimate. The coefficients of variation for the cost attributes are 2.15 and 3.57 for investment cost and monthly cost, respectively. The *z*-value for the standard deviation is highest for these two attributes, suggesting a high degree of confidence in the shape of this distribution and the degree of heterogeneity.

[9] $£1 * \frac{1-0.998^{12*20}}{1-0.998} = £229$

[10] $£12 * \frac{1-0.98^{20}}{1-0.98} = £199$

Preferences for the three attributes of replacement period, CO2 emissions, and job creation are also significantly heterogeneous, with coefficients of variation of 2.38, 1.46, and 1.56 respectively. The *z*-value for the standard deviation for the job creation attribute is the least significant, implying a lower degree of confidence in the shape of the distribution.

We can also use the mean and standard deviation from the mixed logit model to investigate whether preferences are heterogeneous to the extent that a significant proportion of the sample has coefficients of the opposite sign. The probability of a negative coefficient on the replacement period is 0.261, implying that 26.1% of respondents prefer heating systems with a shorter replacement period. This may be because this would allow them to upgrade their heating system more regularly, potentially to achieve gains in efficiency which come through product research and development over time.

The probability of a positive coefficient on CO2 emissions is 0.247, implying that 24.7% of respondents prefer heating systems with higher CO2 emissions. This result conflicts with the hypothesis that households will derive negative marginal utility from CO2 emissions due to the adverse environmental consequences. To test whether this is a true reflection of underlying preference or just a by-product of the assumption of normally distributed preferences, we compare the fit of this model against models with different distributional assumptions. In Appendix C4 we estimate model D1, where we assume a normal distribution with a restricted standard deviation, such that only 10% of the population has positive coefficients. In model D2, we assume a log-normal distribution. The likelihood ratio test rejects model D1 in favour of model 2, and the Ben-Akiva and Swait test is in favour of model D2 over model 2. This leads us to conclude that log-normal is a superior estimation of the distribution of preferences for CO2 emissions, which implies that preferences are negative across the whole sample.

In model 2, the probability of a negative coefficient on job creation is 0.337, implying that 33.7% of respondents oppose job creation. Again, this result conflicts with the hypothesis that households will derive positive marginal utility from job creation due to the social benefits job opportunities provide. We repeated the tests above for the job creation coefficient, testing both a normal distribution with a restricted standard deviation and a log-normal distribution. Both the model with a restricted normal distribution and the model with the log-normal rejected the normal distribution in model 2, with the log-normal distribution having the highest log-likelihood. This leads us to conclude that preferences for job creation are positive across the whole sample.

The log-likelihood of our MXL is significantly higher than the simple MNL model, demonstrating that this model better fits our data. The Ben-Akiva and Swait test returns a p-value of virtually zero, highlighting the degree to which the MXL model is superior.

3.5.3 Multinomial and Mixed Logit with Socio-demographic Characteristics Model Analysis

To unpack this heterogeneity, we investigate the impact of different socio-demographic and housing characteristics, focusing on income, gender, education, employment status, age, and key housing characteristics such as whether they own their accommodation, how long they have lived in their accommodation, and long they expect to live in their accommodation in the future.

Column 1 of Table 3.5 shows the MNL with socio-demographics. We include socio-demographic and housing characteristics as shift parameters on household preferences for the alternative-specific constants of the different heating system attributes, using *'pum'* as the baseline. To investigate the impact of income, we include a categorical variable 'low income', which identifies households with aggregate income below £30,000. We find that income has a significant effect on preferences for job creation, with those with lower income having a higher preference. Since there is no significant effect of either of the cost attributes, this implies low-income households have a higher willingness to pay for job creation.

'Own accommodation' indicates whether the households own their housing either outright or with a mortgage, 'time10' indicates whether households have lived in their accommodation for 10 or more years, whilst 'exptime10' indicates whether households expect to live in their accommodation for 10 or more years. Interestingly, the only significant influence on the cost coefficients is that those who have lived in their accommodation for 10 or more years have an even higher aversion to investment costs. The only other significant effect of housing characteristics on preference is that homeowners have a lower preference for job creation, implying a lower willingness to pay.

'*Male*' is a categorical variable indicating whether the respondent is male and '*Unemp*' indicates whether the respondent is unemployed, we find these have no significant effect on preferences. '*UniEduc*' indicates whether the respondent has graduated from university, we find that this only influences preferences for CO2 emissions, whereby those with a university education are more averse to CO2 emissions. Since their cost parameter is not significantly affected, this implies that they would have a higher willingness to pay for heating systems with lower CO2 emissions.

Finally, we find that age has a significant effect on preferences. We looked at the difference across three different age groups: under 35 years old, 35 to 55 years old, and over 55 years old, where over 55 years old is the base group in the regression. These years were chosen based on the history of coal mining, with the youngest group largely being born after the closure of the mines (or too young to remember them) (1991-1994[11]), the middle group being children when the mines were open (1969-1989), and the final group being adults who were likely to have worked in the mines or to have known people who worked in the mines. We find that the respondent's age has a significant effect on preferences. Both of the younger groups appear less cost-sensitive to both investment and monthly costs. The middle 35-55 group is also less sensitive to CO_2 emissions and job creation. This implies that due to lower investment cost-sensitivity, the youngest group will have a higher willingness to pay for heating system attributes, whilst the middle group may have a higher or lower willingness to pay for lower CO_2 emissions and job creation, depending on the relative changes in sensitivities towards these attributes compared to the cost attributes.

When we include both random and deterministic heterogeneity in the MXL model with socio-demographics, we discover two important things. Firstly, we find that when random unobserved heterogeneity is controlled for, some of the sociodemographic variables become significant. Secondly, we see that the significance of the variance terms is reduced, demonstrating that the inclusion of deterministic factors for observed heterogeneity reduces random heterogeneity.

Both of these factors can be seen in the investment cost attribute. We can see that in column 2 of table 3.5, low income now has a positive, significant effect on sensitivity to investment cost. Counterintuitively, this implies that low-income households are less sensitive to cost attributes, and thus appear to have a more elastic demand for heating systems. We can also see that whilst there is still significant variance in the distribution of the income preference parameter, its estimation accuracy has reduced from having a *z*-value of 35.44 to 17.17, which is still very high.

We can also see that by introducing deterministic heterogeneity in the model, the variance of the random parameter estimates on the job creation attribute becomes insignificant. This suggests that heterogeneity is adequately captured by these socio-demographics, where age and university education have significant effects on preference parameters.

[11] Closure of large mines Dawdon, Murton, Van Tempest, Westoe, Easington, Wearmouth, Ellington (UK Parliament, Mine Closures).

Table 3.5: Estimation of Multinomial Logit with socio-demographics (Model 3) and Mixed Logit with socio-demographics (Model 4)

	MNL with socio-demographics (Model 3)	**MXL with socio-demographics** (Model 4)
ASC_{geo}	1.576 (5.55)***	-0.016 (0.05)
ASC_{hyd}	1.393 (4.15)***	-1.018 (2.36)**
ASC_{sol}	1.120 (3.53)***	1.520 (4.38)***
ASC_{pum}	0.000 (fixed)	0.000 (fixed)
$\beta_{InvCost}$	-0.820 (2.72)***	1.819 (31.02)*** {0.000638}[1]
$\sigma_{InvCost}$		-0.609 (12.78)*** {-0.000480}[1]
$\beta_{MonCost}$	-0.727 (5.76)***	0.459 (5.90)*** {-0.0280}[1]
$\sigma_{MonCost}$		1.006 (12.55)*** {-0.0465}[1]
β_{RepPer}	0.348 (2.88)***	0.420 (2.64)***
σ_{RepPer}		0.0742 (9.28)***
β_{CO2}	0.643 (3.08)***	-1.725 (2.85)***
σ_{CO2}		3.772 (13.99)***
β_{Job}	0.852 (1.93)*	1.317 (2.02)**
σ_{Job}		0.920 (1.06)
α^{geo}_{LowInc}	-0.038 (0.24)	0.273 (1.43)
α^{sol}_{LowInc}	-0.067 (0.37)	0.317 (1.30)
α^{hyd}_{LowInc}	-0.096 (0.59)	-0.265 (1.47)
$\alpha^{InvCost}_{LowInc}$	0.164 (0.93)	1.442 (4.76)***
$\alpha^{MonCost}_{LowInc}$	-0.069 (0.96)	0.151 (1.53)
α^{RepPer}_{LowInc}	0.030 (0.44)	0.047 (0.49)
α^{CO2}_{LowInc}	-0.040 (0.29)	-0.078 (0.24)
α^{Job}_{LowInc}	0.525 (2.09)**	0.657 (1.83)*
$\alpha^{geo}_{OwnAccom}$	-0.052 (0.29)	0.384 (1.83)*
$\alpha^{sol}_{OwnAccom}$	-0.068 (0.33)	0.492 (1.81)*
$\alpha^{hyd}_{OwnAccom}$	0.193 (0.92)	-0.040 (0.18)
$\alpha^{InvCost}_{OwnAccom}$	-0.103 (0.52)	1.278 (3.57)***
$\alpha^{MonCost}_{OwnAccom}$	0.113 (1.41)	0.356 (2.92)***
$\alpha^{RepPer}_{OwnAccom}$	-0.110 (1.40)	-0.099 (-0.91)

$\alpha_{\text{OwnAccom}}^{\text{CO2}}$	0.116 (0.84)	0.173 (0.32)
$\alpha_{\text{OwnAccom}}^{\text{Job}}$	-0.579 (1.94)*	-0.509 (1.20)
$\alpha_{\text{Time10}}^{\text{geo}}$	0.007 (0.04)	0.443 (1.94)*
$\alpha_{\text{Time10}}^{\text{sol}}$	0.082 (0.39)	0.621 (2.14)**
$\alpha_{\text{Time10}}^{\text{hyd}}$	-0.015 (0.08)	-0.297 (1.32)
$\alpha_{\text{Time10}}^{\text{InvCost}}$	-0.407 (2.02)**	1.034 (3.00)***
$\alpha_{\text{Time10}}^{\text{MonCost}}$	-0.137 (1.67)*	0.044 (0.34)
$\alpha_{\text{Time10}}^{\text{RepPer}}$	-0.012 (0.16)	-0.047 (0.42)
$\alpha_{\text{Time10}}^{\text{CO2}}$	-0.138 (0.90)	-0.278 (0.60)
$\alpha_{\text{Time10}}^{\text{Job}}$	-0.149 (0.53)	-0.209 (0.50)
$\alpha_{\text{ExpTime10}}^{\text{geo}}$	-0.086 (0.55)	0.164 (0.81)
$\alpha_{\text{ExpTime10}}^{\text{sol}}$	0.055 (0.29)	0.479 (1.83)*
$\alpha_{\text{ExpTime10}}^{\text{hyd}}$	-0.206 (1.18)	-0.370 (1.84)*
$\alpha_{\text{ExpTime10}}^{\text{InvCost}}$	-0.009 (0.05)	1.138 (3.81)***
$\alpha_{\text{ExpTime10}}^{\text{MonCost}}$	-0.101 (1.32)	0.082 (0.72)
$\alpha_{\text{ExpTime10}}^{\text{RepPer}}$	0.086 (1.18)	0.113 (1.06)
$\alpha_{\text{ExpTime10}}^{\text{CO2}}$	-0.092 (0.61)	-0.543 (1.34)
$\alpha_{\text{ExpTime10}}^{\text{Job}}$	0.032 (0.12)	-0.173 (0.44)
$\alpha_{\text{Male}}^{\text{geo}}$	-0.296 (2.04)**	-0.084 (0.47)
$\alpha_{\text{Male}}^{\text{sol}}$	-0.352 (2.06)**	0.005 (0.02)
$\alpha_{\text{Male}}^{\text{hyd}}$	-0.107 (0.68)	-0.280 (1.60)*
$\alpha_{\text{Male}}^{\text{InvCost}}$	-0.192 (1.15)	0.867 (3.03)***
$\alpha_{\text{Male}}^{\text{MonCost}}$	0.008 (0.11)	0.167 (1.59)*
$\alpha_{\text{Male}}^{\text{RepPer}}$	-0.051 (0.78)	-0.081 (0.871)
$\alpha_{\text{Male}}^{\text{CO2}}$	-0.145 (1.12)	-0.341 (1.00)
$\alpha_{\text{Male}}^{\text{Job}}$	0.114 (0.46)	0.109 (0.32)
$\alpha_{\text{UniEd}}^{\text{geo}}$	-0.047 (0.32)	0.113 (0.62)
$\alpha_{\text{UniEd}}^{\text{sol}}$	-0.001 (0.01)	0.250 (1.08)
$\alpha_{\text{UniEd}}^{\text{hyd}}$	-0.121 (0.79)	-0.247 (1.43)
$\alpha_{\text{UniEd}}^{\text{InvCost}}$	-0.135 (0.76)	0.436 (1.36)
$\alpha_{\text{UniEd}}^{\text{MonCost}}$	-0.064 (0.87)	-0.049 (0.44)
$\alpha_{\text{UniEd}}^{\text{RepPer}}$	-0.009 (0.13)	0.040 (0.41)
$\alpha_{\text{UniEd}}^{\text{CO2}}$	-0.425 (2.95)***	-1.170 (3.16)***
$\alpha_{\text{UniEd}}^{\text{Job}}$	0.501 (1.86)*	0.858 (2.19)**

$\alpha_{\text{Unemp}}^{\text{geo}}$	0.021 (0.08)	-0.027 (0.08)
$\alpha_{\text{Unemp}}^{\text{sol}}$	-0.218 (0.64)	-0.230 (0.48)
$\alpha_{\text{Unemp}}^{\text{hyd}}$	-0.095 (0.33)	-0.222 (0.66)
$\alpha_{\text{Unemp}}^{\text{InvCost}}$	0.439 (1.36)	0.547 (0.98)
$\alpha_{\text{Unemp}}^{\text{MonCost}}$	0.141 (0.97)	0.291 (1.28)
$\alpha_{\text{Unemp}}^{\text{RepPer}}$	-0.181 (1.39)	-0.288 (1.63)
$\alpha_{\text{Unemp}}^{\text{CO2}}$	0.601 (2.77)***	0.718 (1.24)
$\alpha_{\text{Unemp}}^{\text{Job}}$	-0.449 (0.89)	-0.821 (1.10)
$\alpha_{\text{Age35}}^{\text{geo}}$	-0.836 (3.44)***	-0.154 (0.54)
$\alpha_{\text{Age35}}^{\text{sol}}$	-0.875 (3.08)***	0.113 (0.31)
$\alpha_{\text{Age35}}^{\text{hyd}}$	-0.383 (1.37)	-0.631 (2.12)**
$\alpha_{\text{Age35}}^{\text{InvCost}}$	-0.005 (0.02)	2.307 (5.86)***
$\alpha_{\text{Age35}}^{\text{MonCost}}$	0.197 (1.78)*	0.771 (5.64)***
$\alpha_{\text{Age35}}^{\text{RepPer}}$	0.021 (0.20)	-0.003 (0.02)
$\alpha_{\text{Age35}}^{\text{CO2}}$	0.195 (1.01)	0.451 (0.77)
$\alpha_{\text{Age35}}^{\text{Job}}$	-0.412 (1.00)	-0.910 (1.55)
$\alpha_{\text{Age3555}}^{\text{geo}}$	-0.377 (1.62)	0.253 (0.91)
$\alpha_{\text{Age3555}}^{\text{sol}}$	-0.240 (0.88)	0.698 (1.97)**
$\alpha_{\text{Age3555}}^{\text{hyd}}$	-0.140 (0.53)	-0.417 (1.47)
$\alpha_{\text{Age3555}}^{\text{InvCost}}$	0.214 (0.93)	2.307 (7.37)***
$\alpha_{\text{Age3555}}^{\text{MonCost}}$	0.019 (0.19)	0.450 (3.87)***
$\alpha_{\text{Age3555}}^{\text{RepPer}}$	-0.003 (0.04)	0.011 (0.08)
$\alpha_{\text{Age3555}}^{\text{CO2}}$	0.257 (1.60)	0.678 (1.36)
$\alpha_{\text{Age3555}}^{\text{Job}}$	-0.736 (2.11)**	-1.017 (2.04)**
LL	-12,396.79	-10,312.18

*With absolute values of z-statistics in brackets, * 90% confidence, ** 95% confidence, *** 99% confidence correspond with 2-sided critical values 1.64, 1.96, 2.58 respectively.*

[1]*Moments of the log-normal estimations in curly brackets, where* μ_β *and* σ_β *are calculated as in table 3.4.*

3.5.4 ICLV: Environmental and Energy Attitudes Model Analysis

To unpack this heterogeneity further, we investigate how respondents' attitudes towards the environment and energy influence their sensitivity towards cost and CO2 emission attributes.

We investigate the above-mentioned attitudes by means of latent variables and interact these with the alternative specific constants and each of the attributes. We find pro-environmental attitudes and energy-saving attitudes have a significant effect on respondents' choices, and significantly improve the fit of the choice model.

Table 3.6.1 Estimation of Measurement equations of the Latent Variable Model for Environmental Attitude within Models 5a and 5b

Environmental Attitude		
	ICLV Env Ene (Model 5a: MNL)	**ICLV Env Ene** (Model 5b: MXL)
η^{concEnv}	-0.422 (3.86)***	-0.402 (3.88)***
τ_1^{concEnv}	-3.865 (16.55)***	-4.064 (17.00)***
τ_2^{concEnv}	-2.782 (18.51)***	-2.984 (18.34)***
τ_3^{concEnv}	-1.526 (14.05)***	-1.738 (14.19)***
τ_4^{concEnv}	0.719 (7.32)***	0.497 (5.09)***
$\eta^{\text{changeLife}}$	-0.309 (3.11)***	-0.457 (4.40)***
$\tau_1^{\text{changeLife}}$	-3.932 (16.19)***	-4.217 (16.86)***
$\tau_2^{\text{changeLife}}$	-2.871 (18.73)***	-3.148 (18.38)***
$\tau_3^{\text{changeLife}}$	-1.698 (16.27)***	-1.959 (14.94)***
$\tau_4^{\text{changeLife}}$	0.916 (10.60)***	0.712 (6.95)***
$\eta^{\text{shouldChange}}$	-0.430 (4.01)***	-0.474 (4.37)***
$\tau_1^{\text{shouldChange}}$	-4.036 (15.87)***	-4.3 (15.86)***
$\tau_2^{\text{shouldChange}}$	-3.23 (18.06)***	-3.492 (17.53)***
$\tau_3^{\text{shouldChange}}$	-1.753 (15.04)***	-2.011 (14.85)***
$\tau_4^{\text{shouldChange}}$	0.652 (6.80)***	0.409 (3.99)***
*With absolute values of robust z-statistics in brackets, * 90% confidence, ** 95% confidence, *** 99% confidence correspond with 2-sided critical values 1.64, 1.96, 2.58 respectively.* *Bolduc et al. (2005) normalisation applied.*		

Table 3.6.2: Estimation of the Measurement equation of Latent Variable Model for Energy Attitude within Models 5a and 5b

Energy Attitude		
	ICLV Env Ene (Model 5a: MNL)	**ICLV Env Ene** (Model 5b: MXL)
$\eta^{\text{adjThermKnow}}$	0.384 (4.29)***	2.226 (10.00)***
$\tau_1^{\text{adjThermKnow}}$	-3.365 (18.28)***	-5.176 (10.59)***
$\tau_2^{\text{adjThermKnow}}$	-2.566 (18.42)***	-4.058 (9.08)***
$\tau_3^{\text{adjThermKnow}}$	-2.009 (17.14)***	-3.254 (7.58)***
$\tau_4^{\text{adjThermKnow}}$	0.133 (1.48)	0.296 (0.74)
$\eta^{\text{adjThermHave}}$	0.308 (3.49)***	1.609 (10.52)***
$\tau_1^{\text{adjThermHave}}$	-3.742 (17.21)***	-4.861 (12.15)***
$\tau_2^{\text{adjThermHave}}$	-2.454 (18.87)***	-3.305 (10.27)***
$\tau_3^{\text{adjThermHave}}$	-1.642 (15.91)***	-2.273 (7.35)***
$\tau_4^{\text{adjThermHave}}$	0.551 (6.67)***	0.861 (2.92)***
$\eta^{\text{redEnergy}}$	0.472 (4.83)***	3.019 (7.50)***
$\tau_1^{\text{redEnergy}}$	-4.262 (15.86)***	-7.746 (8.32)***
$\tau_2^{\text{redEnergy}}$	-3.074 (18.25)***	-5.759 (7.67)***
$\tau_3^{\text{redEnergy}}$	-2.306 (17.14)***	-4.459 (6.58)***
$\tau_4^{\text{redEnergy}}$	0.216 (2.21)**	0.588 (1.09)
η^{energyDM}	0.594 (6.41)***	1.691 (11.52)***
τ_1^{energyDM}	-4.649 (15.01)***	-5.75 (12.56)***
τ_2^{energyDM}	-3.294 (18.14)***	-4.14 (11.24)***
τ_3^{energyDM}	-2.119 (15.31)***	-2.699 (7.92)***
τ_4^{energyDM}	-0.124 (1.11)	-0.019 (0.06)
*With absolute values of robust z-statistics in brackets, * 90% confidence, ** 95% confidence, *** 99% confidence correspond with 2-sided critical values 1.64, 1.96, 2.58 respectively.* *Bolduc et al. (2005) normalisation applied.*		

Table 3.7.1: Estimation of Structural equation of Latent Variable Model for Environmental Attitude within Models 5a and 5b

Environmental Attitude		
	ICLV Env Ene (Model 5a: MNL)	**ICLV Env Ene** (Model 5b: MXL)
γ_{LowInc}	-0.144 (1.86)*	0.143 (2.07)**
γ_{Male}	-0.004 (0.05)	0.048 (0.69)

γ_{UniEduc}	-0.102 (1.29)	-0.132 (1.78)*
γ_{Unemp}	-0.005 (0.03)	0.266 (1.51)
$\gamma_{\text{Age 35}}$	-0.068 (0.56)	0.44 (3.50)***
γ_{Age3555}	0.058 (0.51)	0.396 (3.58)***
γ_{OwnAccom}	0.109 (1.19)	0.14 (1.32)
γ_{Renew}	-0.079 (0.53)	0.38 (2.22)**
γ_{Time10}	0.057 (0.61)	0.021 (0.25)
$\gamma_{\text{ExpTime10}}$	-0.012 (0.13)	0.029 (0.36)
*With absolute values of robust z-statistics in brackets, * 90% confidence, ** 95% confidence, *** 99% confidence correspond with 2-sided critical values 1.64, 1.96, 2.58 respectively.*		

Table 3.7.2: Estimation of Structural equation of Latent Variable Model for Energy Attitude within Model 5a and 5b

Energy Attitude		
	ICLV Env Ene (Model 5a: MNL)	**ICLV Env Ene** (Model 5b: MXL)
γ_{LowInc}	-0.140 (1.80)*	-0.218 (2.54)**
γ_{Male}	-0.041 (0.54)	0.143 (1.73)*
γ_{UniEduc}	0.092 (1.22)	0.12 (1.29)
γ_{Unemp}	-0.214 (1.38)	-0.328 (1.57)
$\gamma_{\text{Age 35}}$	-0.522 (3.96)***	-0.51 (3.52)***
γ_{Age3555}	-0.306 (2.74)***	-0.199 (1.56)
γ_{OwnAccom}	0.026 (0.27)	0.235 (2.39)**
γ_{Renew}	-0.527 (4.28)***	-0.336 (1.98)**
γ_{Time10}	0.187 (2.11)**	0.013 (0.13)
$\gamma_{\text{ExpTime10}}$	0.081 (0.95)	0.316 (3.30)***
*With absolute values of robust z-statistics in brackets, * 90% confidence, ** 95% confidence, *** 99% confidence correspond with 2-sided critical values 1.64, 1.96, 2.58 respectively.*		

Tables 3.6.1, 3.6.2, 3.7.1 and 3.7.2 show the parameter estimates of the latent variable model, with the first column showing results from the ICLV with an MNL choice model (Model 5a), and the second showing results from the ICLV with an MXL choice model (Model 5b). Tables 3.6.1 and 3.6.2 show the measurement equation estimates for each of the latent variables (equations 3.21 and 3.22). As expected from the factor analysis in Table 3.2, all the indicators are statistically significant. All the environmental attitudinal indicators reflect pro-environmental attitude; therefore, since their coefficients are negative in Table 3.6.1, a higher value of the environmental latent variable reflects a lower concern for the well-being of the environment. All the energy attitudinal indicators reflect energy-

saving attitudes; therefore, positive coefficients mean that a higher value of the energy latent variable reflects a greater preference to reduce energy usage. Results are consistent between models 5a and 5b.

Tables 3.7.1 and 3.7.2 show the structural equation estimates for both the environmental (equation 3.19) and energy (equation 3.20) latent variables. We estimated the structural equations with a random error term which we simulated with 2000 random Sobel-Faure-Tezuka draws. As expected, the structural equation is weak with few socio-demographic variables having a significant effect on attitudes. Including random parameters in the choice model increases the significance of several parameters. We can see that low income is significant for both behaviours. For environmentally friendly attitudes the sign of the parameter changes when random parameters are introduced into the choice model, this suggests that for individuals with a similar distribution of random parameters, a lower income implies less environmentally friendly attitudes. Model 5b also demonstrates that those with lower income tend to be less energy conscious. University education becomes significant in model 5b, demonstrating a positive relation with environmentally friendly attitudes.

Model 5a suggests that energy attitudes are positively impacted by the length of time that people have lived in their accommodation, whilst model 5b suggests that those who expect to live in their accommodation for a longer time period in the future tend to be more energy conscious.

Surprisingly, those who have installed renewable heating systems in their houses are less environmentally friendly and less energy conscious. One would expect energy-consciousness to be a primary motivation for investing in renewable heating systems. Our results may reflect a boomerang effect, whereby, since their source of heating is renewable and affordable they are no longer concerned with their energy usage, or they feel that they have done their bit for the environment and thus are morally licenced to increase their energy usage.

Finally, we find that energy consciousness increases with age, with those above 55 being the most energy conscious, and those under 35 being the least energy conscious. This could be related to experience and time paying energy bills since older people are more aware of the rise in energy prices. It could also be related to the different lifestyles of different ages, whereby on average retired people spend more time at home, people between 35 and 55 are more likely to be providing for the energy usage of a whole family, and people below 35 may have smaller homes.

Table 3.6: Estimation of Structural Equation of Choice Model within Models 5a and 5b

	MNL (Model 1)		**ICLV Env Ene MNL** (Model 5a)		**ICLV Env Ene MXL** (Model 5b)	
	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.
ASC_{geo}	0.892 (12.32)***	0.045	1.575 (5.13)***	0.307	0.799 (3.76)***	0.212
ASC_{hyd}	0.802 (9.40)***	0.058	1.507 (4.15)***	0.363	-0.053 (0.19)	0.274
ASC_{sol}	0.717 (9.13)***	0.043	0.769 (2.86)***	0.269	-0.366 (1.57)	0.233
ASC_{pum}	0.000 (fixed)	(fixed)	0.000(fixed)	(fixed)	0.000 (fixed)	(fixed)
$\beta_{invCost}$	-0.956 (11.63)***	0.075	-2.300 (10.05)***	0.229	0.869 (5.74)*** {-4.150}[1]	0.151
$\sigma_{invCost}$					1.053 (13.1)*** {1.238}[1]	0.08
$\beta_{monCost}$	-0.758 (22.03)***	0.023	-1.558 (10.08)***	0.155	0.319 (3.28)*** {-2.402}[1]	0.097
$\sigma_{monCost}$					1.056 (14.15)*** {0.456}[1]	0.075
β_{repPer}	0.323 (12.14)***	0.031	0.573 (7.78)***	0.074	0.689 (7.64)***	0.09
σ_{repPer}					0.651 (8.70)***	0.075
β_{co2}	-0.775 (12.14)***	0.053	-1.864 (7.87)***	0.237	-3.084 (8.64)***	0.357
σ_{co2}					2.509 (9.48)***	0.265
β_{job}	0.689 (5.68)***	0.113	1.688 (6.47)***	0.261	2.128 (6.97)***	0.305
σ_{job}					2.481 (6.77)***	0.366
λ_{geo}^{env}			0.643 (2.52)**	0.255	-1.394 (6.52)***	0.214
λ_{hyd}^{env}			1.731 (8.37)***	0.207	0.414 (1.41)	0.294
λ_{sol}^{env}			1.338 (6.81)***	0.197	1.145 (6.11)***	0.188
$\lambda_{invCost}^{env}$			-0.39 (2.21)**	0.176	1.531 (7.66)***	0.200
$\lambda_{monCost}^{env}$			0.591 (5.42)***	0.109	0.546 (7.58)***	0.072
λ_{repPer}^{env}			-0.188 (3.03)***	0.062	-0.348 (4.63)***	0.075
λ_{co2}^{env}			1.096 (7.08)***	0.155	1.373 (7.63)***	0.18
λ_{job}^{env}			-0.949 (3.90)***	0.243	-1.209 (4.72)***	0.256
λ_{geo}^{ene}			1.696 (9.81)***	0.173	0.211 (1.11)	0.19
λ_{hyd}^{ene}			1.394 (7.54)***	0.185	0.879 (3.68)***	0.239
λ_{sol}^{ene}			-0.225 (1.33)	0.169	0.442 (2.30)**	0.192
$\lambda_{invCost}^{ene}$			-0.777 (10.38)***	0.075	-0.182 (3.15)***	0.058
$\lambda_{monCost}^{ene}$			-1.204 (9.19)***	0.131	0.355 (2.10)**	0.169
λ_{repPer}^{ene}			0.274 (4.98)***	0.055	0.136 (2.38)**	0.057
λ_{co2}^{ene}			-0.852 (7.13)***	0.119	-0.504 (3.53)***	0.143
λ_{job}^{ene}			0.565 (2.82)***	0.200	-0.114 (0.57)	0.199

LL (choice model)	-12,611.23	-9,564.05	-9251.21
*Absolute values of robust z-statistics in brackets, * 90% confidence, ** 95% confidence, *** 99% confidence correspond with 2-sided critical values 1.64, 1.96, 2.58 respectively.* [1]*Moments of the log-normal estimations in curly brackets, where* $\mu_\beta = -\exp\left(\mu_{log\,\beta} + \frac{\sigma^2_{log\,\beta}}{2}\right)$, *and* $\sigma_\beta = \mu_\beta * \sqrt{\exp(\sigma^2_{\log\beta}) - 1}$			

Table 3.8 shows the structural equation estimates for the choice models (equations 3.23-3.25). In the first column, we have replicated the model 1 MNL results from Table 3.4 above. We used these values as starting values in the estimation of model 5a and the MXL results from Table 3.4 as the starting values in the estimation of model 5b. In the second column, we have estimated the MNL choice model from model 5a. In the third column, we have estimated the MXL choice model from model 5b. We find that the estimates for the parameters change significantly compared to model 1 and that the environmental and energy latent variables have a significant effect on the alternative specific constants and respondents' sensitivity to all attributes.

We observe consistent findings regarding the influence of the environmental latent variable on individuals' aversion to CO2 emissions across models 5a and 5b. The environmental latent variable has a positive effect on the sensitivity to CO2 emissions, this suggests that weaker pro-environmental attitudes lead to lower disutility from CO2 emissions. Conversely, those with stronger pro-environmental attitudes are more averse to CO2 emissions.

The influence of environmental attitudes on sensitivity to investment cost differs between models 5a and 5b. In model 5a (MNL), the interaction parameter is negative, implying that individuals with stronger pro-environmental attitudes are less sensitive to investment costs. In contrast, in model 5b (MXL) this interaction parameter becomes positive, indicating that, on average, individuals with stronger pro-environmental preferences are more sensitive to investment costs. The significance of the standard deviation of the investment cost parameter demonstrates significant preference heterogeneity within the sample. The change of sign on the interaction term between environmental preferences and the investment cost parameter upon introduction of random parameters suggests that for individuals with a common distribution of random parameters, those with higher environmental preferences tend to be more cost-sensitive. Whilst, at the population level, when these effects are not accounted for, it appears that those with stronger environmental preferences have lower cost sensitivity. This suggests that incorporating random parameters controls for omitted variable bias, implying that there are some underlying characteristics which correlate with environmental attitudes and influence cost sensitivity.

For example, it could be that those who have stronger environmental preferences are people who have more leisure time to spend in nature and have sufficient education and financial capacity to care about contributing to the environment. In this sense, this group of people would likely have a lower cost consciousness, since they have space, time and money to spend time in and contribute to nature, but this cost sensitivity is not caused by their environmental attitudes.

The overall effect of environmental attitudes on willingness to pay for cleaner heating systems depends on how the ratio of emissions sensitivity to cost sensitivity varies with environmental attitudes. In model 5a, it is clear to see that at the population level, those with higher environmental attitudes have a higher willingness to pay for cleaner systems, since they are both more sensitive to CO2 emissions and less sensitive to investment cost. Thus, it appears that they are willing to put their money where their values lie. However, this effect is complicated within model 5b, since when controlling for random parameters, those with higher environmentally friendly attitudes are more sensitive to both CO2 emissions and cost, the overall effect will depend on the relative size of these two effects for each individual. This suggests that the positive effect on willingness to pay observed in model 5a is likely to be driven largely by underlying heterogeneity which is correlated to environmental preferences. This suggests that increasing environmental preferences would not be sufficient to encourage the adoption of clean technologies, underlying heterogeneous enabling factors influence the capability of individual to put their money where their values lie.

We find that the environmental attitude latent variable has a negative effect on the sensitivity to the replacement period, reflecting that those who care less about the environment care less about how long their heating system lasts. Given the negative effect on the sensitivity to investment cost in model 5a, this suggests that those who care less about the environment will have a lower willingness to pay for heating systems with longer durations, which implies that those with stronger pro-environmental preferences have a higher willingness to pay. This could reflect efforts to minimise life cycle environmental impact by extending the duration. However, given the positive effect on sensitivity to investment cost in model 5b, it is likely that this effect is driven by underlying factors which are correlated with environmental preferences. Differential time preferences are also suggested by the different signs of the parameters on investment cost and monthly cost in model 5a, which implies that whilst those with heightened environmental attitudes are more sensitive to monthly energy costs, they appear less sensitive to heating system investment costs, this could reflect how those with higher environmental preferences are more willing to save to make high quality investments. This effect disappears in model 5b, implying that this effect is not driven by the latent variable itself, but by random parameters which correlate with it.

We find that the energy attitude latent variable has a negative effect on the sensitivity to CO2 emissions in both model 5a and 5b, reflecting that those who care more about reducing their energy usage are more averse to CO2 emissions. We also find that it has a negative effect on the sensitivity to investment cost in both models 5a and 5b, reflecting that those who are energy-conscious are also more cost-conscious. Overall, energy-conscious attitudes may have a positive or negative effect on willingness to pay for heating systems with lower CO2 emissions, since whilst the CO2 emissions coefficient becomes more negative (increases in absolute size), the investment cost coefficient also becomes more negative (increases in absolute size). Since the magnitude of the change in sensitivity to investment cost is greater, this is likely to reduce willingness to pay for lower CO2 emissions, but this is driven by cost sensitivity rather than lack of concern for CO2 emissions.

We also find that the energy attitude latent variable has a positive effect on the sensitivity to replacement period, reflecting that those who care more about reducing their energy usage care more about how long their heating system lasts. However, given the heightened cost consciousness, they are unlikely to be willing to pay for heating systems that last longer.

In Appendix C5 we investigate whether our model is robust to correlation between the random parameters. We estimate a model 5c which allows for correlation between the random parameter on investment cost and the random parameter on CO2 emissions. We find that the parameter on the correlation term is positive and significant, but that the sign and significance of the sensitivity parameters and latent variable interaction terms retain their sign and significance. This supports our behavioural hypotheses, suggesting that our findings are robust to correlated random parameters. A further investigation of the full matrix of correlation is left for future research.

Overall, model 5a suggests that those who hold strong environmental preferences are willing to put their money where their values lie and will have a higher willingness to pay for low-carbon heat. Whilst model 5b, suggests that this effect will be heterogeneous across the population, is likely to depend on some enabling factors, and is not guaranteed to increase willingness to pay. These models also imply that the primary motivation behind energy-saving attitudes is to save money with the secondary motive being to reduce emissions, which suggests that energy-conscious households may be less inclined to pay for low-carbon heat. Given that we have not studied how changes in attitudes over time influence stated preferences for heating systems, from our study we cannot directly infer how changes in environmental or energy attitudes may influence willingness to pay (Chorus and Kroesen, 2014).

3.5.5 ICLV: Coal Mining Identity Model Analysis

To investigate how local coal mining heritage may influence participants' preferences towards repurposing coal mines for renewable heating technologies and towards the creation of green jobs, we introduce coal mining identity into an ICLV model as a latent variable. We look at the influence of the latent variable measuring coal mining identity on the alternative specific constants and each of the attribute parameters.

Table 3.7: Estimation of Measurement Equation of Latent Variable Model within Model 6a and 6b

Coal Mining Identity		
	ICLV MNL (Model 6a)	ICLV MXL (Model 6b)
$\eta^{\text{idenHerit}}$	-0.096 (1.34)	0.021 (0.27)
$\tau_1^{\text{idenHerit}}$	-2.492 (19.57)***	-2.516 (19.24)***
$\tau_2^{\text{idenHerit}}$	-1.226 (15.05)***	-1.252 (14.28)***
$\tau_3^{\text{idenHerit}}$	0.043 (0.62)	0.014 (0.19)
$\tau_4^{\text{idenHerit}}$	1.435 (16.49)***	1.404 (15.49)***
η^{honHist}	0.235 (3.11)***	0.328 (3.90)***
τ_1^{honHist}	-4.164 (15.98)***	-4.297 (16.26)***
τ_2^{honHist}	-2.777 (19.67)***	-2.908 (18.93)***
τ_3^{honHist}	-0.51 (6.58)***	-0.625 (6.84)***
τ_4^{honHist}	1.451 (15.79)***	1.357 (13.86)***
η^{projImp}	0.28 (3.84)***	0.367 (4.44)***
τ_1^{projImp}	-4.33 (15.43)***	-4.477 (15.66)***
τ_2^{projImp}	-3.507 (18.28)***	-3.654 (18.12)***
τ_3^{projImp}	-1.463 (15.63)***	-1.599 (14.91)***
τ_4^{projImp}	0.649 (7.99)***	0.539 (6.00)***
*With absolute z-value in brackets, * 5% sig, ** 2.5% sig. *** 1% sig. Bolduc et al. (2005) normalisation applied.*		

Table 3.8: Estimation of Structural Equation of Latent Variable Model within Model 6

Coal mining identity		
	Hybrid MNL	Hybrid MXL
γ_{LowInc}	0.003 (0.03)	-0.044 (0.55)
γ_{Male}	-0.060 (0.82)	-0.122 (1.61)
γ_{UniEd}	0.093 (1.29)	0.077 (0.96)
γ_{Unemp}	-0.129 (0.85)	-0.081 (0.46)
γ_{Age35}	-0.394 (3.11)***	-0.398 (3.07)***
γ_{Age3555}	-0.261 (2.44)**	-0.388 (3.41)***

γ_{OwnAccom}	-0.092 (1.01)	-0.165 (1.52)
γ_{Time10}	0.158 (1.88)*	0.03 (0.33)
$\gamma_{\text{ExpTime10}}$	0.058 (0.69)	-0.056 (0.62)
γ_{NoMines}	-0.002 (0.86)	-0.003 (1.41)
*Absolute values of robust z-statistics in brackets, * 90% confidence, ** 95% confidence, *** 99% confidence correspond with 2-sided critical values 1.64, 1.96, 2.58 respectively.*		

Tables 3.9 and 3.10 show the estimations of the latent variable model for identity. Table 3.9 shows the measurement equation (as in equations 3.21 and 3.22 but for identity) estimates. The factor analysis in Table 3.2 showed that coal mining identity was a weaker latent variable with a Crombach Alpha value of 0.594. We can see this weakness reflected in lower levels of significance of the indicator variables, with the $\eta^{\text{idenHerit}}$ for the indicator question relating to identifying with the coal mining heritage of the region ('iden_herit') not being statistically significant. This reinforces that we should interpret the results from this ICLV model with caution. All the factor loadings are positive, with both the indicator relating to the repurposing of coal mines honouring the coal mining history of the region ('hon_his'), and the indicator relating to feeling that the GEMS project is good for local communities ('proj_imp'), being significant. This implies that the latent variable may not directly reflect coal mining identity, but more a view that repurposing the mines is good for the community.

Table 3.10 shows the structural equation (equation 3.26) estimates for identity. As in the case of environmental and energy attitudes, the structural equation is relatively weak. We can see that only age is significant, those under the age of 35, who would not have been old enough to remember the mines being open, have the lowest coal mining identity. Whilst those who are older than 55 who were alive whilst the mines were open and during the miners' strike in the 1980s have the strongest identity.

Table 3.9: Estimation of Structural Equation of Choice Model within Model 6

	MNL (Model 1)		**ICLV iden MNL** (Model 6a)		**ICLV iden MXL** (Model 6b)	
	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.
ASC_{geo}	0.892 (12.32)***	0.045	0.894 (3.69)***	0.242	0.743 (3.64)***	0.204
ASC_{hyd}	0.802 (9.40)***	0.058	0.967 (7.60)***	0.127	-0.104 (0.41)	0.258
ASC_{sol}	0.717 (9.13)***	0.043	0.064 (0.51)	0.127	-0.429 (1.83)*	0.234
ASC_{pum}	0.000 (fixed)	(fixed)	0.000 (fixed)	(fixed)	0.000 (fixed)	(fixed)
β_{invCost}	-0.956 (11.63)***	0.075	-1.744 (10.29)***	0.17	0.81 (5.50)***	0.147

					{-4.219}[1]	
σ_{invCost}					-1.122 (12.84)*** {1.286}[1]	0.087
β_{monCost}	-0.758 (22.03)***	0.023	-1.288 (10.22)***	0.126	0.278 (2.99)*** {-2.403}[1]	0.093
σ_{monCost}					1.095 (12.55)*** {0.422}[1]	0.087
β_{repPer}	0.323 (12.14)***	0.031	0.481 (8.00)***	0.06	0.653 (8.37)***	0.078
σ_{dur}					0.64 (8.01)***	0.08
β_{co2}	-0.775 (12.14)***	0.053	-1.437 (7.99)***	0.18	-3.009 (9.95)***	0.302
σ_{co2}					2.497 (10.65)***	0.234
β_{job}	0.689 (5.68)***	0.113	1.628 (7.43)***	0.219	1.952 (6.78)***	0.288
σ_{job}					-2.371 (6.91)***	0.343
$\lambda_{\text{geo}}^{\text{iden}}$			1.614 (10.98)***	0.147	1.501 (7.38)***	0.203
$\lambda_{\text{hyd}}^{\text{iden}}$			0.622 (4.24)***	0.147	-0.2 (0.66)	0.303
$\lambda_{\text{sol}}^{\text{iden}}$			-0.656 (4.80)***	0.137	-1.039 (5.40)***	0.192
$\lambda_{\text{invCost}}^{\text{iden}}$			-0.903 (7.47)***	0.121	-1.396 (6.91)***	0.202
$\lambda_{\text{monCost}}^{\text{iden}}$			-0.795 (17.13)***	0.046	-0.579 (8.53)***	0.068
$\lambda_{\text{repPer}}^{\text{iden}}$			0.263 (5.46)***	0.048	0.35 (4.91)***	0.071
$\lambda_{\text{co2}}^{\text{iden}}$			-1.027 (12.85)***	0.080	-1.25 (8.62)***	0.145
$\lambda_{\text{job}}^{\text{iden}}$			0.791 (4.35)***	0.182	1.008 (4.19)***	0.240
LL (choice model only)	-12,611.23		-10,512,08		-9,418.16	

*Absolute values of robust z-statistics in brackets, * 90% confidence, ** 95% confidence, *** 99% confidence correspond with 2-sided critical values 1.64, 1.96, 2.58 respectively.*

[1]*Moments of the log-normal estimations in curly brackets, where*

$$\mu_\beta = -\exp\left(\mu_{log\,\beta} + \frac{\sigma_{log\,\beta}^2}{2}\right), \textit{ and } \sigma_\beta = \mu_\beta * \sqrt{\exp\left(\sigma_{\log\beta}^2\right) - 1}$$

The choice model in Table 3.11 shows the structural equation estimates of the choice model (equations 3.27-3.29). It demonstrates that the coal mining identity latent variable has a significant effect on both the renewable energy alternative and sensitivity towards the choice attributes.

Firstly, we can see from the alternative-specific constants that those with a stronger coal mining identity are significantly more likely to select the geothermal district heating system. This demonstrates that those who feel that repurposing the mines will be good for their community are comparatively more inclined to adopt geothermal district heating over other renewable energy systems. Therefore, communities with stronger coal mining identities are likely to be more receptive to geothermal district heating systems being set up within their communities.

Secondly, we can see that coal mining identity has a significant effect on the sensitivity to all attributes. Of particular interest are the job creation attribute and the investment cost attributes. Participants with stronger coal mining identity have a greater sensitivity towards job creation, demonstrated by a positive coefficient in both models 6a and 6b. On the one hand, this aligns with the narrative of high levels of unemployment and lack of skilled job opportunities within mining communities following the closure of the mines. This would have been felt more acutely by individuals and families who had historically relied on the mines for employment, and thus they would likely feel more strongly about job creation, particularly skilled jobs in the energy sector. On the other hand, given that the identity latent variable could be interpreted as a positive feeling towards repurposing mines for the good of the community, this may reflect how one of the reasons people feel it is good for the community is because of the local job opportunities it will create.

We can also see that those who have a stronger coal mining identity are more cost-sensitive, both in terms of investment cost and monthly cost. This effect holds in both model 6a and model 6b where preference heterogeneity is accounted for. This would also make sense given the history of hardship faced by coal mining communities following the closure of the mines, which is still true at present in the form of comparative economic disadvantage.

In Appendix C5 we investigate whether our model is robust to correlation between the random parameters. We estimate a model 6c which allows for a correlation between the random parameter on investment cost and the random parameter on job creation. We find that the parameter on the correlation term is positive and insignificant, and that the sign and significance of all choice model parameters are unchanged. Again, this supports the robustness of our behavioural hypotheses.

The combination of higher sensitivity to job creation and higher sensitivity to cost may result in a positive or negative influence of coal mining identity on willingness to pay for job creation. Despite having a greater preference for job creation, their cost sensitivity reduces their willingness to pay for everything and may counter this preference. In this case, the proportional increase in cost sensitivity is relatively larger than the proportional increase in sensitivity to job creation, which implies that despite having stronger preferences for job creation, those with stronger coal mining identity have a lower willingness to pay for job creation due to their sensitivity to costs.

This suggests that there is an attitude-behaviour gap in the case of job creation. Individuals with a stronger coal mining identity are more sensitive to job creation, but this heightened sensitivity to cost is a barrier to them expressing this preference in the market, since they would not be willing to pay more for an alternative offering higher job creation due to budgetary constraints.

3.6 Model Predictions

Discrete choice models can be used to predict how consumer behaviour will change in response to policy proposals which influence attribute levels of the alternatives. We use models 5a and 6a to investigate how adoption rates of the technologies change in response to (1) the introduction of a carbon tax, (2) the introduction of technology-specific subsidies. We investigate how the behavioural variables of environmental attitudes, energy-saving attitudes, and coal mining identity relate to the extent of behaviour change.

3.6.1 Carbon Tax Predictions

Carbon taxes are a market intervention which explicitly put a price on the carbon emission externalities arising from production processes and consumption. Ideally, the price of carbon in the market should be set equal to the marginal cost of the externality, such that demand for pollutive products is discouraged through higher prices to the extent that externalities are internalised. Within this study, we apply the UK carbon price of £83.05 per tonne of CO2 emissions.

To investigate the influence of a carbon tax on the probability of choosing different heating system technologies, we look at the effect of adding the carbon tax to investment cost and monthly cost separately. In scenario 1, we add the carbon tax to the investment cost; to do so we calculate the annual cost of CO2 emissions by multiplying emissions by the carbon price. We then calculate the total value of emissions by adding up the cost of CO2 emissions and discounting them over the replacement period of the product.

$$\mathrm{InvCostCP}_i = \mathrm{InvCost}_i + \mathrm{CO2}_i * 0.08305 * \left(\frac{(1+r)^{\mathrm{RepPer}_i} - 1}{r * (1+r)^{\mathrm{RepPer}_i}} \right) \tag{3.30}$$

Where '*InvCostCP*' is the investment cost inclusive of the carbon tax, and r is the discount rate, which we set to 0.02.

We separately look at what would happen if we charged the carbon tax as part of the monthly cost of the heating systems. In scenario 2, we add the carbon tax to the monthly cost, by first dividing the annual CO2 emissions by 12, and then multiplying them by the carbon price.

$$\mathrm{MonCostCP_i} = \mathrm{MonCost_i} + \left(\frac{1}{12}\right) * \mathrm{CO2_i} * 0.08305 \tag{3.31}$$

Where *'MonCostCP'* is the monthly cost inclusive of the carbon tax. We then use models 5a and 6a to predict, for each respondent in each choice task, the probability of selecting each alternative in scenario 1 and scenario 2. We compare the probabilities within each scenario with the base probabilities to see how charging a carbon tax would influence demand across the different technologies.

The carbon tax increases the cost of all alternatives in proportion to the carbon emissions they produce, therefore heating systems which release more carbon dioxide on average will become relatively more expensive. Table 3.12 shows that for both models 5a and 6a, the pattern of demand change is similar, with the average probability of selecting geothermal district heating rising the most and the average probability of selecting hydrogen boilers decreasing the most under both scenarios. This is likely to reflect that on average geothermal district heating releases lower CO2 emissions, thus in response to a carbon tax respondents shift their demand to this cleaner alternative.

Table 3.10: Predicted average probability of selecting each alternative when a carbon tax is introduced

		Geothermal District Heating	Hydrogen boiler	Solar electric boiler	Air source heat pump
ICLV: Env and Ene Attitudes (Model 5)	No Tax	0.4688	0.2511	0.1897	0.0904
	Carbon Tax on Investment Cost	0.5122	0.2031	0.1928	0.0920
	Carbon Tax on Monthly Cost	0.4866	0.2332	0.1905	0.0899
ICLV: Identity (Model 6)	No Tax	0.4669	0.2464	0.1876	0.0992
	Carbon Tax on Investment Cost	0.4990	0.2097	0.1945	0.0967
	Carbon Tax on Monthly Cost	0.4848	0.2253	0.1908	0.0991

We investigate the patterns of heterogeneity underlying the changes in probabilities of selecting each alternative, focusing on how the change in probability of selecting geothermal district heating varies across the different latent variables. We first calculate the difference in probabilities (before and after carbon tax) of selecting geothermal district heating for each respondent in each choice task, we then run an OLS regression to regress this difference against the conditional value of each of the latent variables both in the base period and in the relevant carbon tax model. Since the ICLV model simultaneously predicts the choice model and the latent variable model, changing attribute levels of the alternatives in the choice model influences the conditional values of the attitudinal variables in the latent variable models. Appendix C6.1 shows that, when a carbon tax is introduced, environmental attitudes strengthen, and energy-saving attitudes and coal-mining identity weaken.

In the case of environmental attitudes, Appendix C6.2 shows that the higher the value of the latent variable, and thus the lower the respondents' pro-environmental attitude, the larger the shift of respondents' demand is towards geothermal district heating. This implies that those with higher pro-environmental attitudes are less responsive to price changes linked to emissions and thus have less elastic demand. This is likely to be because these respondents already choose the cleaner alternative.

In the case of energy-saving attitudes, Appendix C6.2 shows that the higher the value of the latent variable, and thus the higher the individuals' energy-saving attitude, the larger the predicted shift of their demand towards geothermal district heating. This reflects the relationship between higher energy-saving attitudes and greater cost-consciousness since the relatively lower price of cleaner heating alternatives is more attractive to respondents with strong energy-saving attitudes.

In the case of coal mining identity, we find that the relationship between the value of the latent variable and the degree to which demand is predicted to shift towards geothermal district heating is statistically insignificant.

In the long run, the effect of a carbon tax on the adoption of different technologies is likely to change. Since a carbon tax makes alternatives with higher CO_2 emissions less competitive in the market, energy companies and manufacturers of renewable heating systems will have a greater incentive to reduce the carbon emissions from production and usage. For example, hydrogen boilers release more CO_2 on average within this choice experiment because brown hydrogen production has high CO_2 emissions, however, as production of hydrogen transitions to green hydrogen and CO_2 emissions fall, the carbon tax would likely favour the adoption of hydrogen boilers. Similarly, solar panels have a high lifecycle CO_2 emission because China is a major supplier of solar panels and coal still makes up a significant proportion of their total energy production. If China transitions their energy production to more renewable sources or if people purchase more from cleaner suppliers, then the carbon tax would be in favour of solar panels.

3.6.2 Technology-specific Subsidy Predictions

Subsidies are a form of market intervention which reduce the price of a given alternative with the objective of increasing its demand. Subsidies are widely applied in the renewable heating sector to encourage the installation of heat pumps and solar panels. Subsidies could be a useful policy to coordinate market behaviour to encourage greater adoption of a given technology in a particular region. For example, in the North East, the abundance of disused coal mining infrastructure makes geothermal heating systems a viable alternative. However, since geothermal heating from mines is set up in district heating systems, adoption by a majority within a given locality is necessary for optimal benefits to be obtained. A subsidy imposed on geothermal district heating systems could coordinate households to purchase a common renewable heating solution.

To investigate the influence of subsidies on demand for the different heating systems, we use model 5 and impose subsidies of 10%, 20%, 50% and 75% on the investment cost of each alternative separately, and predict the probability of each technology being chosen.

Table 3.11: Predicted average probability of selecting each alternative when a subsidy is introduced on the investment cost of each alternative in turn

	Geothermal District Heating	Hydrogen boiler	Solar electric boiler	Air source heat pump
No subsidy	0.4688	0.2511	0.1897	0.0904
Geothermal				
10%	0.4799	0.2431	0.1880	0.0890
20%	0.4911	0.2351	0.1863	0.0875
50%	0.5245	0.2109	0.1813	0.0834
75%	0.5516	0.1910	0.1773	0.0800
Hydrogen				
10%	0.4635	0.2576	0.1893	0.0896
20%	0.4582	0.2642	0.1889	0.0887
50%	0.4391	0.2880	0.1873	0.0857
75%	0.4270	0.3028	0.1864	0.0838
Solar Electric boiler				
10%	0.4593	0.2566	0.1951	0.0889
20%	0.4552	0.2547	0.2017	0.0884

50%	0.4403	0.247	0.2261	0.0865
75%	0.4236	0.2381	0.2536	0.0847
Air source heat pump				
10%	0.4602	0.2559	0.1888	0.0952
20%	0.4571	0.2530	0.1882	0.1017
50%	0.4421	0.2394	0.1852	0.1333
75%	0.4288	0.2270	0.1828	0.1614

Table 3.13 suggests that if these were the only heating systems available on the market, then subsides will have an influence upon which heating system is adopted, however, this influence is quite small. For example, subsidising geothermal district heating by 50% only increases the probability of adoption from 49.11% to 52.45%. The largest effects are seen for air source heat pumps, which is the technology that has the lowest probability of adoption in the base model. Here, a 50% subsidy increases adoption from 9.52% to 13.33%, increasing adoption by around 40%.

3.7 Key Findings and Conclusion

Household adoption of renewable heating systems is fundamental for the UK to achieve its net zero commitments. The government identified that it is unlikely that there is a one-size-fits-all solution (BEIS, 2018) and that multiple technologies will be important on our path to net zero. On the supply side, suitable technologies depend upon natural resources, environment and climate. For example, the North East of England is endowed with disused coal mines offering potential for geothermal district heating systems. On the demand side, household preferences have a significant influence on the adoption of available renewable heating systems. 78% of households in the UK have natural gas boilers and adoption of renewable heating systems is likely to be delayed due to households wanting to exploit the lifetime of their current heating system. Key barriers to investing in renewable heating systems are the higher cost and lack of familiarity with new technologies.

We conducted a choice experiment where respondents were faced with a scenario in which they were choosing a new heating system for a new residential accommodation, with no status quo option. We present households with four different renewable heating systems, geothermal district heating, a hydrogen boiler, a solar electric boiler, and an air source heat pump. We vary the attribute levels of investment cost, monthly cost, replacement period, CO2 emissions and job creation. We analyse the trade-offs respondents make between the alternatives in the different choice tasks to investigate marginal willingness to pay for the different product attributes. We investigate the heterogeneity of household preferences by analysing how socio-demographic characteristics and latent variables measuring environmental and energy attitudes and coal mining identity influence sensitivities towards the different attributes.

We find that the most preferred renewable heating alternative is geothermal district heating. We also find that all product attributes have a significant influence on respondents' utility and thus on the alternative they choose.

Of significant interest is the marginal willingness to pay for CO2 reduction. A key aim of the energy transition is to reduce the carbon footprint of heating systems. To understand household willingness to pay to contribute to achieving this aim, it is important to see to what extent households are willing to voluntarily internalise the externalities arising from their heating consumption. We find that the marginal willingness to pay for lower CO2 emissions is £27.27 - £40.54 (depending on time discounting) per tonne of CO2 which is less than half of the 2023 UK carbon price of £83.05. This implies that external intervention is necessary to fully internalise negative environmental externalities. We find that environmental and energy attitudes increase sensitivity towards CO2 emissions and that whilst those with stronger pro-environmental attitudes have a higher marginal willingness to pay for CO2 emission reduction, those with strong energy-saving attitudes have a lower marginal willingness to pay due to their higher cost sensitivity. We also find that when we introduce random parameters into our ICLV choice model, heightened sensitivity to CO2 emissions remains for both latent variables, but neither has discernible effects of willingness to pay, suggesting that underlying random parameters that are related to environmental attitudes are driving observed heightened willingness to pay.

We also investigate marginal willingness to pay for job creation, finding that on average respondents are willing to pay £72.07 per additional job created when 1000 households adopt the technology. When aggregated over 1000 households, this amount is close to the average cost of job creation calculated by the IFS 2023. We find that those who have a stronger coal mining identity or feel more positive about the impact that repurposing coal mines would have upon the local community feel more strongly about job creation, however, their higher cost sensitivity means that they would not have a higher willingness to pay for this job creation. We also found that these households were more likely to choose geothermal district heating within our choice experiment scenario.

Finally, we have predicted how the choice of heating system will change with the introduction of a carbon tax and a subsidy. Our two integrated choice and latent variable models predict that the carbon tax will encourage respondents to adopt geothermal district heating. Respondents with stronger energy-saving attitudes have the most elastic demand, whilst respondents with stronger pro-environmental attitudes have the least elastic demand. We also find that subsidising technologies does increase demand for that technology, but that even subsidising at 75% only increases demand for geothermal by 7.2%, hydrogen boilers by 4.5%, solar panels by 5.9% and air source heat pumps by 6.6%. In the current market, with gas boilers still being the cheapest available alternative, these proportions are likely to be even smaller.

Understanding the behavioural determinants driving the adoption of renewable heating systems and addressing attitude-behaviour gaps are critical for promoting sustainable energy practices and shaping effective policies. This study demonstrates that environmental and energy attitudes, as well as social identity, play a significant role in how households evaluate heating system attributes and prioritize collective social benefits. These insights provide valuable guidance for designing targeted interventions and policies that align with household values, thereby facilitating the transition to sustainable energy systems.

References

Abesser, C. and Walker, A., 2022. Geothermal energy. *UK Parliament POSTbrief 46, 27/04/2022.* https://doi.org/10.58248/PB46

Abou-Zeid, M., Ben-Akiva, M., 2011. The effect of social comparisons on commute well-being. *Transportation Research Part A, 45, 345-361.* https://doi.org/10.1016/j.tra.2011.01.011

Abou-Zeid, M., Ben-Akiva, M., 2024. Hybrid choice models. *Handbook of Choice Modelling, Ed. Hess., S., Daly, A., Edward Elgar Publishing. Chapter 18, 489-521.* https://doi.org/10.4337/9781800375635.00026

Ajzen, I., 1991. The theory of planned behaviour. *Organisational Behaviour and Human Decision Processes, 50, 2, 179-211.* https://doi.org/10.1016/0749-5978(91)90020-T

Akerlof, G.A., Kranton, R.E., 2000. Economics and Identity. *The Quarterly Journal of Economics, 115, 3.* https://doi.org/10.1162/003355300554881

Albuquerque, R., Koskinen, Y., Yang, S., Zhang, C., 2020. Resiliency of Environmental and Social Stocks: An analysis of the exogenous COVID-19 market crash. *The Review of Corporate Finance Studies, 9, 3, 593-621.* https://doi.org/10.1093/rcfs/cfaa011

Alesina, A., Giuliano, P., 2015. Culture and Institutions. *Journal of Economic Literature, 53, 4, 898-944.* https://doi.org/10.1257/jel.53.4.898

Alger, I., Weibull, J.W., 2013. Homo Moralis- Preference Evolution under Incomplete Information and Assortative Matching. *Econometricia, 81, 6, 2269-2302*. https://doi.org/10.3982/ECTA10637

Alger, I., Weibull, J.W., 2016. Evolution and Kantian Morality. *Games and Economic Behaviour, 98, 56-67*. https://doi.org/10.1016/j.geb.2016.05.006

Alger, I., Weibull, J.W., Lehmann, L., 2020. Evolution of preferences in structured populations: Genes, guns, and culture. *Journal of Economic Theory, 185, 104951.* https://doi.org/10.1016/j.jet.2019.104951

Amador, F.J., González, R.M., Ramos-Real, F.J., 2013. Supplier choice and WTP for electricity attributes in an emerging market: the role of perceived past experience, environmental concern and energy saving behaviour. *Energy Economics, 40, C, 953-966.* https://doi.org/10.1016/j.eneco.2013.06.007

Ambec, S., De Donder, P., 2022. Environmental Policy with Green Consumerism. *Journal of Environmental Economics and Management, 111, 1-17.* https://doi.org/10.1016/j.jeem.2021.102584

Anable, J., 2005. 'Complacent Car Addicts' or 'Aspiring Environmentalists'? Identifying travel behaviour segments using attitude theory. *Transport Policy 12, 65-78.* https://doi.org/10.1016/j.tranpol.2004.11.004

Andreoni, J., 1989. Giving with Impure Altruism: Applications to Charity and Ricardian Equivalence. *Journal of Political Economy, 97, 6, 1447-1458*. https://doi.org/10.1086/261662

Andreoni, J., 1990. Impure Altruism and Donations to Public Goods: A Theory of Warm-Glow Giving. *The Economic Journal, 100, 401, 464-477.* https://doi.org/10.2307/2234133

Andreoni, J., Rao, J.A., Trachtman, H., 2017. Avoiding the Ask: A Field Experiment on Altruism, Empathy, and Charitable Giving. *Journal of Political Economy, 125, 3, 625-653*. https://doi.org/10.1086/691703

Anwar, M., Tieu, K., Gibson, P., Berryman, M.J., Win, K.T., McCusker, A., Perez, P., 2014. Temporal and parametric study of traveller preference heterogeneity using random parameter logit model. *International Journal for Traffic and Transport Engineering, 4, 4, 437-455. :* http://dx.doi.org/10.7708/ijtte.2014.4(4).07

Aravena, C., Riquelme, A., Denny, E., 2016. Money, Comfort or Environment? Priorities and determinants of energy efficient investments in Irish households. *Journal of Consumer Policy, 39, 159-186.* https://doi.org/10.1007/s10603-016-9311-2

Ardia, D., Bluteau, K., Boudt, K., Inghelbrecht, K., 2022. Climate Change Concerns and the Performance of Green vs. Brown Stocks. *Management Science, 69, 12, 7607-7632*. https://doi.org/10.1287/mnsc.2022.4636

Arifin, W.N., 2017 Exploratory factor analysis and Cronbach's alpha. *Questionnaire Validation Workshop, 10/10/2017, USM Health Campus, Universiti Sains Malaysia.* https://wnarifin.github.io/workshop/qvw2017/efa.pdf Last visited: 03/12/2024.

Arrow, K.J., 1973. Social Responsibility and Economic Efficiency. *Public Policy, 21, 303-317.* https://arrunada.org/files/t/gom1/Arrow%201973%20Social%20Responsb%20%20&%20Econ%20Effccy.pdf

Ashok, K., Dillon, R., Yuan, S., 2002. Extending discrete choice models to incorporate attitudinal and other latent variables. *Journal of Marketing Research, 39, 1, 31-46.* https://doi.org/10.1509/jmkr.39.1.31.18937

Ayoubi, C., Thurm, B., 2020. Pro-environmental behaviour and morality: an economic model with heterogeneous preferences. *OSF Preprints w8afg, Center for Open Science*. https://doi.org/10.31219/osf.io/w8afg

Baker, M., Bergstresser, D., Serafeim, G., Wurgler, J., 2022. The Pricing and Ownership of U.S. Green Bonds. *Annual Review of Financial Economics, 14, 1-23*. https://doi.org/10.1146/annurev-financial-111620-014802

Banks, D., Athresh, A., Al-Habaibeh, A., and Burnside, N., 2019. Water from abandoned mines as a heat source: practical experiences of open- and closed-loop strategies, United Kingdom. *Sustainable Water Resources Management, 5, 1, 29–50*. https://doi.org/10.1007/s40899-017-0094-7

Barber, B., Morse, A., Yasuda, A., 2021. Impact Investing. *Journal of Financial Economics, 139, 1, 162-185*. https://doi.org/10.1016/j.jfineco.2020.07.008

Bauer, R., Ruof, T., Smeets, P., 2021. Get Real! Individuals prefer more sustainable investments. *The Review of Financial Studies, 34, 8, 3976-4043*. https://doi.org/10.1093/rfs/hhab037

Beatty, C., Fothergill, S., Fore, T., 2019. The State of the Coalfields 2019: economic and social conditions in the former coalfields of England, Scotland and Wales. *Centre for Regional Economic and Social Research, Sheffield Hallam University.* https://shura.shu.ac.uk/25272/1/state-of-the-coalfields-2019.pdf

Beckers, K. F. and Young, K. R., 2017. Performance, Cost, and Financial Parameters of Geothermal District Heating Systems for Market Penetration Modeling under Various Scenarios. *Technical report, National Renewable Energy Laboratory (NREL), Stanford.* https://pangea.stanford.edu/ERE/pdf/IGAstandard/SGW/2017/Beckers.pdf

Ben-Akiva, M., Bolduc, D., 1996. Multinomial probit with a logit kernel and a general parametric specification of the covariance structure. *D'epartement d'economique, Universit'e laval with Department of Civil and Environmental Engineering, Massachusetts Institute of Technology. https://eml.berkeley.edu/reprints/misc/multinomial.pdf*

Ben-Akiva, M., Bolduc, D., Bradley, M., 1993. Estimation of travel choice models with randomly distributed values of time. *Transportation Research Record, 1413, 88-97.* http://onlinepubs.trb.org/Onlinepubs/trr/1993/1413/1413-010.pdf

Ben-Akiva, M., McFadden, D., Gärling, T., Gopinath, D., Walker, J., Bolduc, D., Börsch-Supan, A., Delquié, P., Larichev, O., Morikawa, T., Polydoropoulou, A., Rao, V., 1999. Extended Framework for Modelling Choice Behaviour. *Marketing Letters 10, 3, 187-203.* https://doi.org/10.1023/A:1008046730291

Ben-Akiva, M., Walker, J., Bernardino, A.T., Gopinath, D.A., Morikawa, T., Polydoropoulou, A., 2002. Integration of Choice and Latent Variable Models. *In Perpetual Motion: Travel Behaviour Research Opportunities and Application Challenges, H.s. Mahmassani, ed., 431-470, Elsevier, Amsterdam.* https://doi/org/10.1016/B978-008044044-6/50022-X

Bergstrom, T.C., 1995. On the Evolution of Altruistic Ethical Rules for Siblings. *The American Economic Review*, 85, 1, 58-81. https://www.jstor.org/stable/2117996

Beynon, H., Hudson, R., 2021. The shadow of the mine: coal mining and the end of industrial Britain. *Verso, London and New York.* https://www.versobooks.com/en-gb/products/990-the-shadow-of-the-mine?srsltid=AfmBOooQ7KM6hBSHjAwozLqyXfxbjP4lxKNZcNEJx9p6gw0kcws3mwKk

Bhat, C.R., 1998. Accommodating variations in responsiveness to level-of-service measures in travel mode choice modelling. *Transportation Research Part A: Policy and Practice. 32, 7, 495-507.* https://doi.org/10.1016/S0965-8564(98)00011-1

Bhat, C.R., 2000. Flexible model structure for discrete choice analysis. *Handbook of Transport Modelling. Edited by D.A. Hensher and K.J. Button, Elsevier Science, 71-90.*

Bhat, C.R., Dubey, S.K., 2014. A new estimation approach to integrate latent psychological constructs in choice modelling. *Transportation Research Part B: Methodological, 67, 68-85.* https://doi.org/10.1016/j.trb.2014.04.011

Bleicher, A. and Gross, M., 2016. Geothermal heat pumps and the vagaries of subterranean geology: Energy independence at a household level as a real world experiment. *Renewable and Sustainable Energy Reviews, 64, 279-288.* https://doi.org/10.1016/j.rser.2016.06.013

Bolduc, D., Ben-Akiva, M., Walker, J., Michaud, A., 2005. Hybrid choice models with logit kernel: applicability to large scale models. *Integrated Land-Use and Transportation Models. Editors Lee-Gosselin, M.E.H., Doherty, S.T., Emerald Group Publishing Limited, Leeds, 275-302.* https://doi.org/10.1108/9781786359520-012

Bollen, N.P.B., 2007. Mutual Fund Attributes and Investor Behaviour. *The Journal of Financial and Quantitative Analysis, 42, 3, 683-708*. https://doi.org/10.1017/s0022109000004142

Bolton, P., Kacperczyk, M., 2021. Do Investors Care about Carbon Risk? *Journal of Financial Economics, 142, 2, 517-549*. https://doi.org/10.1016/j.jfineco.2021.05.008

Bonnefon, J. F., Landier, A., Sastry, P.R., Thesmar, D., 2022. The moral preferences of investors: experimental evidence. *NBER Working Paper 29647*. https://www.nber.org/papers/w29647

Borchers, A.M., Duke, J.M., Parsons, G.R., 2007. Does willingness to pay for green energy differ by source? *Energy Policy, 35, 6, 3327-3334.* https://doi.org/10.1016/j.enpol.2006.12.009

Bovenberg, A.L., de Mooij, E.A., 1994. Environmental Levies and Distortionary Taxation. *The American Economic Review, 84, 4, 1085-1089*. https://www.jstor.org/stable/2118046

Bovenberg, A.L., van der Ploeg, F., 1994. Environmental Policy, Public Finance and the Labour Market in a Second-Best World. *Journal of Public Economics, 55, 3, 349-390.* https://doi.org/10.1016/0047-2727(93)01398-T

Boyce, C., Czajkowski, M., Hanley, N., 2019. Personality and economic choices. *Journal of Environmental Economics and Management, 94, 92-100.* https://doi.org/10.1016/j.jeem.2018.12.004

Boyd, J.H., Mellman, R.E., 1980. The effect of fuel economy standards on the U.S. automotive market: a hedonic demand analysis. *Transportation Research Part A: General, 14, 5-6, 367-378.* https://doi.org/10.1016/0191-2607(80)90055-2

Bradley, M., Daly, A., 1994. Use of the logit scaling approach to test for rank-order and fatigue effects in stated preference data. *Transportation, 21, 2, 167–184.* https://doi.org/10.1007/BF01098791

Brécard, D., 2013. Environmental Quality Competition and Taxation in the Presence of Green Network Effect Among Consumers. *Environmental & Resource Economics, 54, 1, 1-19* https://doi.org/10.1007/s10640-012-9576-0

Brekke, K.A., Kvendoff, S., Nyborg, K., 2003. An Economic Model of Moral Motivation. *Journal of Public Economics, 87, 9-10, 1967-1983*. https://doi.org/10.1016/S0047-2727(01)00222-5

British Gas, 2024. Hydrogen boilers: everything you need to know. https://www.britishgas.co.uk/the-source/greener-living/hydrogen-heating.html Last viewed: 03/12/2024

Brooks, L.J., 1989. Corporate Ethical Performance: Trends, Forecasts and Outlooks. *Journal of Business Ethics, 8, 31-38*. https://doi.org/10.1007/bf00382014

Brown, R.W., 1986. Social Psychology, The Second Edition. *The Free Press, A Division of Macmillan, Inc., New York.*

Brownstone, D., Train, K., 1998. Forecasting new product penetration with flexible substitution patterns. *Journal of Econometrics, 89, 1-2, 109-129*. https://doi.org/10.1016/S0304-4076(98)00057-8

Burkardt, J., 2023. The Truncated Normal Distribution. *Department of Scientific Computing, Florida State University*. https://people.sc.fsu.edu/~jburkardt/presentations/truncated_normal.pdf

Campbell, D., Hutchinson, W.G., Scarpa, R., 2009. Using choice experiments to explore the spatial distribution of willingness to pay for rural landscape improvements. *Environmental and Planning A: Economy and Space, 41, 1.* https://doi.org/10.1068/a4038

Campbell, D., Scarpa, R., Hutchinson, W.G., 2008. Assessing the spatial dependence of welfare estimates obtained from discrete choice experiments. *Letters in Spatial and Resource Sciences, 1, 117-126, 97-111.* https://doi.org/10.1007/s12076-008-0012-6

Caparo, V., Rand, D.G., 2018. Do the Right Thing: Experimental evidence that moral behaviour, rather than equity or efficiency per se, drive human prosociality. *Judgement and Decision Making, 13, 1, 99-111*. https://doi.org/10.2139/ssrn.2965067

Cardell, N.S., Dunbar, F.C., 1980. Measuring the societal impacts of automobile downsizing. *Transportation Research Part A: General. 14, 5-6, 423-434.* https://doi.org/10.1016/0191-2607(80)90060-6

Caussade, S., Ortuzar, J.D., Rizzi, L.I., Hensher, D.A., 2005. Assessing the influence of design dimensions on stated choice experiment estimates. *Transportation Research Part B: Methodological, 39, 7, 621-640.* https://doi.org/10.1016/j.trb.2004.07.006

Ceccarelli, M., Ramelli, S., Wagner, A.F., 2023. Low Carbon Mutual Funds. *Review of Finance, 28, 1, 45-74*. https://doi.org/10.1093/rof/rfad015

Census, 2021. https://www.nomisweb.co.uk/query/construct/submit.asp?forward=yes&menuopt=201&subcomp=

Chesser, M., Lyons, P., O'Reilly, P., and Carroll, P., 2021. Air source heat pump in-situ performance. *Energy and Buildings, 251, 111365*. https://doi.org/10.1016/j.enbuild.2021.111365

Chipman, J.S., 1960. Stochastic choice and subjective probability. *Decisions, values and groups, Vol. 1, Editor D. Willner, Pergamon, New York.*

Choi, D., Gao, Z., & Jiang, W., 2020. Attention to global warming. *Review of Financial Studies, 33, 3, 1112–1145*. https://doi.org/10.1093/rfs/hhz086

Cicia, G., Cembalo, L., Giudice, T.D., Palladino, A., 2012. Fossil energy versus nuclear, wind, solar and agricultural biomass: Insights from an Italian national survey. *Energy Policy, 42, 59-66.* https://doi.org/10.1016/j.enpol.2011.11.030

Clarke, G. (2019). Heat pumps v Oil and Gas. A complete no-brainer! https://les.mitsubishielectric.co.uk/the-hub/heat-pumps-v-oil-and-gas Last visited: 03/12/2024

Claudy, M.C., Michelsen, C., O'Driscoll, A., 2011. The diffusion of microgeneration technologies-assessing the influence of perceived product characteristics on homeowners' willingness to pay. *Energy Policy, 39, 3, 1459-1469.* https://doi.org/10.1016/j.enpol.2010.12.018

Claudy, M., Peterson, M., O'Driscoll, A., 2013. Understanding the Attitude-Behaviour Gap for Renewable Energy Systems using Behavioural Reasoning Theory. *Journal of Macromarketing, 33, 4, 273.* https://doi.org/10.1177/0276146713481605

Collier, P., 2016. The cultural foundations of economic failure: a conceptual toolkit. *Journal of Economic Behaviour and Organisation, 126, 5-24.* https://doi.org/10.1016/j.jebo.2015.10.017

Cremer, H., Gahvari, F., Ladoux, N., 2003. Environmental taxes with heterogeneous consumers: an application to energy consumption in France. *Journal of Public Economics, 87, 2791-2815.* https://doi.org/10.1016/S0047-2727(02)00081-6

Crossley, R., 2023. Air Source Heat Pump Servicing Costs. https://refurbb.co.uk/household/air-source-heat-pump-servicing/#:~:text=Air%20source%20heat%20pump%20servicing%20will%20cost%20in%20the%20region,London%20and%20the%20South%20East. Last visited: 03/12/2024

Curry, P.A., Roemer, J.E., 2012. Evolutionary Stability of Kantian Optimisation. *Review of Public Economics, 200, 1, 131-146.* https://doi.org/10.2139/ssrn.2112098

Czajkowski, M., Hanley, N., Nyborg, K., 2017. Social Norms, Morals, and Self-interest as Determinants of Pro-environmental Behaviours: The Case of Household Recycling. *Environmental Resource Economics, 66, 647-670.* https://doi.org/10.1007/s10640-015-9964-3

Daly, A., Bess, S., Patruni, B., Potoglou, D., Rohr, C., 2012. Using ordered attitudinal indicators in a latent variable choice model: a study of the impacts of security on rail behaviour. *Transportation, 39, 267-297.* https://doi.org/10.1007/s11116-011-9351-z

Dam, L., 2011. Socially Responsible Investment in an Environmental Overlapping Generations Model. *Resource and Energy Economics, 33, 1015-1027.* https://doi.org/10.1016/j.reseneeco.2010.08.002

Dam, L., Heijdra, B.J., 2011. The Environmental and Macroeconomic Effects of Socially Responsible Investment. *Journal of Economic Dynamics and Control, 35, 9, 1424-1434*. https://doi.org/10.2139/ssrn.1159680

Dam, L., Scholtens, B., 2015. Toward a theory of responsible investing: on the economic foundations of corporate social responsibility. *Resource and Energy Economics, 41, C, 103-121*. https://doi.org/10.1016/j.reseneeco.2015.04.008

Dasgupta, P., Southerton, D., Ulph, A., Ulph, D., 2016. Consumer Behaviour with Environmental and Social Externalities: Implications for Analysis and Policy. *Environmental Resource Economics, 65, 191-26*. https://doi.org/10.1007/s10640-015-9911-3

Daziano, R.A., Bolduc, D., 2013. Incorporating pro-environmental preferences towards green automobile technologies through a Bayesian hybrid choice model. *Transportmetrica, 9, 1, 74-106.* https://doi.org/10.1080/18128602.2010.524173

Debreu, G., 1960. Review of R.D. Luce Individual Choice Behaviour: A theoretical analysis. *American Economic Review, 50, 186-188.*

Deloitte, 2023. The Sustainable Consumer 2023. https://www.deloitte.com/uk/en/Industries/consumer/research/sustainable-consumer.html Last visited: 22/08/2024. Last visited: 03/12/2024

Department for Business, Energy & Industrial Strategy, 2018. Clean Growth- Transforming Heating: Overview of current evidence. https://assets.publishing.service.gov.uk/media/5c191c05ed915d0b9211b9c5/decarbonising-heating.pdf Last visited: 03/12/2024

Department for Business, Energy & Industrial Strategy, 2021a. Heat and Buildings Strategy. HM Government. https://www.gov.uk/government/publications/heat-and-buildings-strategy Last visited: 03/12/2024

Department for Business, Energy and Industrial Strategy, 2021b. BEIS Public Attitudes Tracker, Winter 2021, UK. https://www.gov.uk/government/statistics/beis-public-attitudes-tracker-winter-2021 Last visited: 03/12/2024

Department of Energy & Climate Change, 2014. UK Solar PV Strategy Part 2: Delivering a Brighter Future. *Technical report*. https://assets.publishing.service.gov.uk/media/5a7d7c0240f0b64fe6c23fec/uk_solar_pv_strategy_part_2.pdf Last visited: 03/12/2024

Department for Environment, Food and Rural Affairs, 2021. Defra Group Research and Innovation Interests 2021. *Research* https://www.gov.uk/government/publications/defra-group-research-and-innovation-interests-2021/defra-group-research-and-innovation-interests *Last visited: 05/12/2024*

Diamond, P.A., 1973. Consumption Externalities and Imperfect Pricing. *The Bell Journal of Economics and Management Science,* 4, 2, 526-538. https://doi.org/10.2307/3003052

Diamond, P.A., 1975. A Many-Person Ramsey Tax Rule. *Journal of Public Economics, 4, 4, 335-342.* https://doi.org/10.1016/0047-2727(75)90009-2

Diamond, P.A., Mirrlees, J.A., 1971. Optimal Taxation and Public Production 1: Production Efficiency. *The American Economic Review, 61, 1, 8-27.* https://www.jstor.org/stable/1910538

Duflo, E., 2017. The Economist as Plumber. *American Economic Review, 107, 5, 1-26.* https://doi.org/10.1257/aer.p20171153

Dunlap, R.E., Van Liere, K.D., Mertig, A.G., Jones, R.E., 2000. Measuring endorsement of an ecological worldview: A revised NEP scale. *Social Science Quarterly, 56, 3, 425-442.* https://doi.org/10.1111/0022-4537.00176

EcoExperts, 2024. Solar Panel Costs UK 2024. https://www.theecoexperts.co.uk/solar-panels/cost

Edgeworth, F.Y. (1881) Mathematical Psychics: An Essay on the Application of Mathematics to the Moral Sciences. *London C. Kegan Paul and Co.*

Eichner, T., Pethig, R., 2022. Kantians Defy the Economists' Mantra of Uniform Pigouvian Emissions Taxes. *Ecological Economics, 200, 107514*. https://doi.org/10.1016/j.ecolecon.2022.107514

Elias, J., Lacetera, N., Macis, M., 2016. Efficiency-Morality Trade-offs in Repugnant Transactions: A Choice Experiment. *NBER Working Paper Series, 22632*. https://doi.org/10.3386/w22632

Elster, J., 1989. Social Norms and Economic Theory. *Journal of Economic Perspectives, 3, 4, 99-117.* https://doi.org/10.1257/jep.3.4.99

Engle, R., Giglio, S., Kelly, B., Lee, H., & Stroebel, J., 2020. Hedging climate change news. *Review of Financial Studies, 33, 3, 1184–1216*. https://doi.org/10.1093/rfs/hhz072

Erdem, T., 1996. A dynamic analysis of market structure based on panel data. *Marketing Science, 15, 4, 359-378.* https://www.jstor.org/stable/184170

Eurosif, 2016. European SRI Study. https://www.eurosif.org/wp-content/uploads/2022/03/Eurosif-SRI-study-2016.pdf

Everitt, B.S., 1984. An Introduction to Latent Variable Models. *Monographs on Statistics and Applied Probability, Chapman and Hall Ltd, New York.*

Faccioli, M., Czajkowski, M., Glenk, K., Martin-Ortega, J., 2020. Environmental attitudes and place identity as determinants of preferences for ecosystem services. *Ecological Economics, 174, 106600.* https://doi.org/10.1016/j.ecolecon.2020.106600

Falk, A., Becker, A., Dohmen, T., Enke, B., Huffman, D., Sunde, U., 2018. Global evidence on economic preferences. *Quarterly Journal of Economics, 133, 1645-1692*. https://doi.org/10.1093/qje/qjy013

Falk, A., Becker, A., Dohmen, T., Huffman, D., and Sunde, U., 2023. The preference survey module: A validated instrument for measuring risk, time, and social preferences. *Management Science, 69,4, 1935-2545*. https://doi.org/10.1287/mnsc.2022.4455

Fascì, M. L., 2022. Air-, ground-and dual-source heat pumps: a comparison between energy-efficient systems for a Swedish dwelling. In E3S Web of Conferences, volume 362. EDP Sciences. https://doi.org/10.1051/e3sconf/202236202001

Fernandez, L., 2024. Estimated number of employees in the solar photovoltaic industry in the United Kingdom (UK) 2014 to 2022. *Statistica.* https://www.statista.com/statistics/960666/employment-solar-pv-united-kingdom-uk/

Ferrini, S., Scarpa, R., 2007. Designs with a priori information for non-market valuation with choice experiments: a Monte Carlo study. *Journal of Environmental Economics and Management, 53, 3, 342-363.* https://doi.org/10.1016/j.jeem.2006.10.007

Franceschinis, C., Scarpa, R., Thiene, M., Rose, J., Moretto, M., Cavalli, R., 2016. Exploring the spatial heterogeneity of individual preferences for ambient heating systems. *Energies, 9, 6, 407.* https://doi.org/10.3390/en9060407

Franceschinis, C., Thiene, M., Scarpa, R., Rose, J., Moretto, M., Cavalli, R., 2017. Adoption of renewable heating systems: an empirical test of the diffusion of innovation theory. *Energy, 125, 313-326.* https://doi.org/10.1016/j.energy.2017.02.060

Frey, B.S., Stutzer, A., 2008. Environmental Morale and Motivation, '*The Cambridge Handbook of Psychology and Economic Behaviour', Ed. Lewis, A., Cambridge University Press*. https://doi.org/10.1017/CBO9780511490118

Gadenne, D., Sharma, B., Kerr, D., Smith, T., 2011. The influence of consumers' environmental beliefs and attitudes on energy saving behaviours. *Energy Policy, 39, 12, 7684-7694.* https://doi.org/10.1016/j.enpol.2011.09.002

Gatersleben, B., Murtagh, N., Abrahamse, W., 2014. Values, identity and pro-environmental behaviour. *Contemporary Social Science, 9, 4, 374-392.* https://doi.org/10.1080/21582041.2012.682086

Gates, B., 2021. How to avoid a climate disaster. The solutions we have and the breakthroughs we need. *Penguin Books Limited.* https://www.penguin.co.uk/books/317490/how-to-avoid-a-climate-disaster-by-gates-bill/9780141993010

Geological Society of London, 2019. Can Abandoned Mines heat our future? *Jan 9, 2019.* https://blog.geolsoc.org.uk/2019/01/09/can-abandoned-mines-heat-our-future/#:~:text=The%20water%20within%20the%20mines,comfortable%2040%2D50°C. Last visited 21/08/2024

Grafton, Q.R., Kompas, T., Long, N.V., 2017. A Brave New World? Kantian-Nashian Interaction and the Dynamics of Global Climate Change Mitigation. *European Economic Review, 99, C, 31-42.* https://doi.org/10.1016/j.euroecorev.2017.04.002

Green, P., 1984. Hybrid models for conjoint analysis: an expository review. *Journal of Marketing Research, 21, 155-169.* https://doi.org/10.1177/002224378402100204

Grosfeld, I., Rodnyansky, A., Zhuravskaya, E., 2013. Persistent antimarket culture: a legacy of the pale of settlement after the Holocaust. *American Economic Journal: Economic Policy, 5, 3, 189-26.* https://www.jstor.org/stable/43189345

Gudmundsson, O., Thorsen, J. E., and Zhang, L., 2013. Cost analysis of district heating compared to its competing technologies. *WIT Transactions on Ecology and the Environment, 176, 107–118*. https://doi.org/10.2495/ESUS130091

Habib, K.N., Tian, Y., Zaman, H., 2011. Modelling commuting mode choice with explicit consideration of carpool in the choice set formation. *Transportation, 38, 4, 587-604.* https://doi.org/10.1007/s11116-011-9333-1

Hansla, A., Gamble, A., Juliusson, A., Gärling, T., 2008. The relationships between awareness of consequences, environmental concern, and value orientations. *Journal of Environmental Psychology, 29, 1-9.* https://doi.org/10.1016/J.JENVP.2007.08.004

Harris, B. and Walker, A., 2023. Heat pumps POSTnote 699. *Technical report, Parliamentary Office of Science and Technology, London*. https://doi.org/10.58248/PN699

Harris, K.M., Meane, M.P., 1999. A model of health plan choice: inferring preferences and perceptions from a combination of revealed preference and attitudinal data. *Journal of Econometrics, 89, 131-157.* https://doi.org/10.1016/S0304-4076(98)00058-X

Hart, D., Howes, J., Lehner, F., Dodds, P., Hughes, N., Fais, B., Sabio, N., and Crowther, M., 2015. Scenarios for deployment of hydrogen in contributing to meeting carbon budgets and the 2050 target. *Climate Change Committee, technical report.* *https://www.theccc.org.uk/wp-content/uploads/2015/11/E4tech-for-CCC-Scenarios-for-deployment-of-hydrogen-in-contributing-to-meeting-carbon-budgets.pdf*

Hartzmark, S. M., Sussman, A. B., 2019. Do investors value sustainability? A natural experiment ranking and fund flows. *The Journal of Finance, 74, 6, 2789-2837.* https://doi.org/10.1111/jofi.12841

Heptonstall, P. and Winskel, M., 2023. Decarbonising Home Heating: An Evidence Review of Domestic Heat Pump Installed Costs. *UK Energy Research Centre, technical report.* *https://ukerc.rl.ac.uk/publications/research_report/UKERC_Decarbonising-Home-Heating_Evidence-Review.pdf*

Hess, S., Beharry-Borg, N., 2012. Accounting for latent attitudes in willingness to pay studies: the case of coastal water quality improvements in Tobago. *Environmental and Resource Economics, 52, 1, 109-131.* https://doi.org/10.1007/s10640-011-9522-6

Hess, S., Hensher, D., Daly, A.J., 2012. Not bored yet- revisiting respondent fatigue in stated choice experiments. *Transportation Research Part A, 46, 3, 626-644.* *https://doi.org/10.1016/j.tra.2011.11.008*

Hess, S., Palma, D., 2019a. Apollo: a flexible, powerful and customisable freeware package for choice model estimation and application. *Journal of Choice Modelling, 32, 100170.* https://doi.org/10.1016/j.jocm.2019.100170

Hess, S., Palma, D., 2019b. Apollo version 0.3.3, user manual. www.ApolloChoiceModelling.com

Hong, H., Kacperczyk, M., (2009) The Price of Sin: The Effects of Social Norms on Markets. *Journal of Financial Economics, 93, 1, 15-36.* https://doi.org/10.1016/j.jfineco.2008.09.001

Howell, B., 2023. The Complete Guide to Solar Panel Maintenance. *The Eco Experts.* https://www.theecoexperts.co.uk/solar-panels/maintenance *Last visited: 03/12/2024*

Hoyos, D., Mariel, P., Fernández-Macho, J., 2009. The influence of cultural identity on the WTP to protect natural resources: some empirical evidence. *Ecological Economics, 68, 2372-2381.*https://doi.org/10.1016/j.ecolecon.2009.03.015

Hoyos, D., Mariel, P., Hess, S., 2015. Incorporating environmental attitudes in discrete choice models: an exploration of the utility of the awareness of consequences scale. *Science of the Total Environment, 505, 1100-1111.* https://doi.org/10.1016/j.scitotenv.2014.10.066

Ideal Heat Solutions, 2023. How Much is an Electric Boiler in the UK? https://www.idealheatsolutions.co.uk/blog/how-much-is-an-electric-boiler/#:~:text=The%20average%20price%20of%20an,well%20as%20the%20installer's%20fees. Last visited: 03/12/2024

Ilhan, E., Sautner, Z., Vilkon, G., 2021. Carbon Tail Risk. *The Review of Financial Studies, 34, 3, 1540-1571.* https://doi.org/10.1093/rfs/hhaa071

Institute of Fiscal Studies, 2023. Spring Budget. https://ifs.org.uk/spring-budget-2023 Last visited: 07.10.2024

ISO Energy, 2023. What are the carbon savings from a heat pump? https://www.isoenergy.co.uk/latest-news/isoenergy-news/carbon-savings-from-a-heat-pump Last visited: 03/12/2024

iStock. Heating water with solar panels stock illustration https://www.istockphoto.com/vector/heating-water-with-solar-panels-gm166078898-21090132 Last accessed: 09/12/2024

Johansson, M.V., Heldt, T., Johansson, P., 2006. The effects of attitudes and personality traits on mode choice. *Transportation Research Part A: Policy and Practice, 40, 6, 507-525.* https://doi.org/10.1016/j.tra.2005.09.001

Jöhreskog, K.G., 1978. Structural analysis of covariance and correlation matrices. *Psychometrika, 43, 443-477.* https://doi.org/10.1007/BF02293808

Kanargianni, M., Ben-Akiva, M., Polydoropoulou, A., 2014. Incorporating social interaction into hybrid choice models. *Transportation, 41, 1263-1285.* https://doi.org/10.1007/s11116-014-9550-5

Kassab, D., 2020. Tax Exemptions of Ethical Products Revisited. *Environmental & Resource Economics, 77, 2, 423-447.* https://doi.org/10.1007/s10640-020-00502-4

Kassahun, H.T., Nicholson, C.F., Jacobsen, J.B., 2016. Accounting for user expectations in the valuation of reliable irrigation water access in the Ethiopian highlands. *Agricultural Water Management, 168, 45-55.* https://doi.org/10.1016/j.agwat.2016.01.017

Kensa Contracting. Kensa Heat Pumps Secure Largest Connect and Notify Approvals. https://www.kensacontracting.com/kensa-heat-pumps-secure-largest-connect-notify-approvals/ Last accessed: 09/12/2024

Koorsgaard, C., 2012. Kant: Groundwork of the Metaphysics of Morals *(2nd ed., Cambridge Tests in the History of Philosophy) (Gregor, M. & Timmermann, J., Trans.) Cambridge: Cambridge University Press.* https://doi.org/10.1017/CBO9780511919978.

Koto, P.S., Yiridoe, E.K., 2019. Expected willingness to pay for wind energy in Atlantic Canada. *Energy Policy, 129, C, 80-88.* https://doi.org/10.1016/j.enpol.2019.02.009

Kranton, R., 2019. The devil is in the details. *Journal of Economic Literature, 57, 1, 147-160.* https://doi.org/10.1257/jel.20171463

Krikser, T., Profeta, A., Grimm, S., and Huther, H., 2020. Willingness-to-pay for district heating from renewables of private households in Germany. *Sustainability, 12, 10, 4129.* https://doi.org/10.3390/su12104129

Laffont, J., 1975. Macroeconomic Constraints, Economic Efficiency and Ethics: An Introduction to Kantian Economics. *Economica, 42, 168, 430-437.* https://doi.org/10.2307/2553800

Lancaster, K., 1966. A new approach to consumer theory. *Journal of Political Economy, 74, 132-157.* https://doi.org/10.1086/259131

Lempriere, M., 2024. Surge in heat pumps and solar drives record for UK homes in 2023. *Carbon Brief, Clear on Climate. https://www.carbonbrief.org/analysis-surge-in-heat-pumps-and-solar-drives-record-for-uk-homes-in-2023/#:~:text=Molly%20Lempriere,-12.01.2024%20%7C%2012&text=Registered%20solar%20photovoltaic%20(PV)%20installations,%25%2C%20reaching%20a%20record%2036%2C799. Last visited: 03/12/2024*

Lewis, A., Cullis, J., 1990. Ethical Investments: Preferences and Morality. *The Journal of Behavioural Economics, 19, 4, 395-411.* https://doi.org/10.1016/0090-5720(90)90025-3

Li, T., Roskilly, A. P., and Wang, Y., 2018. Life cycle sustainability assessment of grid-connected photovoltaic power generation: A case study of Northeast England. *Applied Energy, 227, 465–479.* *https://doi.org/10.1016/j.apenergy.2017.07.021*

Lin, H., Clavreul, J., Jeandaux, C., Crawley, J., and Butnar, I., 2021. Environmental life cycle assessment of heating systems in the UK: Comparative assessment of hybrid heat pumps vs. condensing gas boilers. *Energy and Buildings, 240.* https://doi.org/10.1016/j.enbuild.2021.110865

Lins, K.V., Servaes, H., Tamayo, A., 2017. Social capital, trust, and firm performance: the value of corporate social responsibility during the financial crisis. *The Journal of Finance, 72, 4, 1785-1824.* https://doi.org/10.1111/jofi.12505

Long, N.V., 2016. The Impacts of Other-Regarding Preferences and Ethical Choice on Environmental Outcomes: A Review of the Literature. *Strategic Behaviour and the Environment, 6, 1-2, 1-35.* https://doi.org/10.1561/102.00000065

Long, N.V., 2017. Mixed Strategy Kant-Nash Equilibrium in Games of Voluntary Contributions to a Public Good, *The Theory of Externalities and Public Goods, edited by Buchholz, W., Rüebbelke, D., Springer Cham, 2017, 107-126.* https://doi.org/10.1007/978-3-319-49442-5

Long, N.V., 2019. A Dynamic Game with Interaction between Kantian players and Nashian players. *CESifo Working Paper No. 7729.* https://doi.org/10.2139/ssrn.3422624

Long, N.V., 2020. A Dynamic Game with Interaction between Kantian Players and Nashian Players. *Games in Management Science, International Series in Operations Research and Management Science, edited by Pineau, P.O., Sigué, S., Taboubi, S., Springer, 2020, 249-267.* https://doi.org/10.1007/978-3-030-19107-8_14

Long, N.V., 2021. Dynamic Games of Common-Property Resource Exploitation when Self-Image Matters. *Dynamic Analysis in Complex Economic Environments: Essays in Honour of Christophe Deissenberg, edited by Dawid, H., Arifovic, J., Springer International Publishing, 2021, 81-107.* https://doi.org/10.1007/978-3-030-52970-3_5

Luce, R.D., 1959. Individual Choice Behaviour. *Wiley, New York.*

Mackenzie, K., Di, J., Marsiliani, L., Naga, L., Renström, T., Scarpa, R., *forthcoming.* Willingness to Pay for low-carbon heating systems by households in the North East of England. *Working Paper.*

Maple, 2024.1. Maplesoft. *A division of Waterloo Maple Inc., Waterloo, Ontario.* https://www.maplesoft.com

Mariel, P., Hoyos, D., Artabe, A., Guevara, C.A., 2018. A multiple indicator solution approach to endogeneity in discrete-choice models for environmental valuation. *Science of the Total Environment, 633, 967-980.* https://doi.org/10.1016/j.scitotenv.2018.03.254

Mariel, P., Hoyos, D., Meyerhoff, J., Czajkowski, M., Dekker, T., Glenk, K., Jacobsen, J.B., Liebe, U., Olsen, S.B., Sagebiel, J., Thiene, M., 2021. Environmental Valuation with Discrete Choice Experiments: Guidance on Design, Implementation and Data Analysis. *Springer Briefs in Economics, Springer International Publishing AG.* https://doi.org/10.1007/978-3-030-62669-3

Mariel, P., Meyerhoff, J., 2016. Hybrid discrete choice models: gained insights versus increasing effort. *Science of the Total Environment, 568, 433-443.* https://doi.org/10.1016/j.scitotenv.2016.06.019

Mariel, P., Meyerhoff, J., Hess, S., 2015. Heterogeneous preferences toward landscape externalities of wind turbines- combining choices and attitudes in a hybrid model. *Renewable and Sustainable Energy Reviews, 41, 647-657.* https://doi.org/10.1016/j.rser.2014.08.074

Marschak, J., 1960. Binary choice constraints and random utility indicators. *Stanford Symposium on mathematical methods in the social sciences, Editor A. Kenneth, Stanford University Press, Stanford.* *https://cowles.yale.edu/sites/default/files/files/pub/d00/d0074.pdf*

Marsiliani, L., Naga, L., Renström, T.I., Spararo, L., 2023. Theory of Socially Responsible Investment: A Review. *Assessing the EU Strategy on Green Finance and ESG Factors: An Interdisciplinary Approach, edited by Spataro, L., Quirici, M.C., Iermano, G., Palgrave Macmillan, Springer.* https://doi.org/10.1007/978-3-031-36457-0_2

Maxim, A. and Roman, T., 2019. The status quo's role in improving the estimation of willingness to pay in choice experiments. *European Journal of Sustainable Development, 8,5, 422.* https://doi.org/10.14207/ejsd.2019.v8n5p422

Maxim, A., Jijie, D. T., and Roman, T., 2022. Why Are Households Willing to Pay for Renewable Energy? Lessons From Romania. *Frontiers in Environmental Science, 10.* https://doi.org/10.3389/fenvs.2022.921152

McFadden, D., 1976. The revealed preferences of a public bureaucracy: empirical evidence. *The Bell Journal of Economics, 7, 1, 55-72.* https://doi.org/10.2307/3003190

McFadden, D., 1974. Conditional logit analysis of qualitative choice behaviour. *Frontiers in Econometrics, Editor P. Zarembka, Academic Press, New York, 105-142.*

McFadden, D., 1986. The Choice Theory Approach to Market Research. *Marketing Science, 5, 275-297.* https://www.jstor.org/stable/184004

Mckay, B. (2023). How Long Does a Boiler Last? *Boiler Guide.* https://www.boilerguide.co.uk/boilers/lifespan *Last visited: 03/12/2024.*

Meles, T.H., Ryan, L., Mukherjee, S.C., 2022. Heterogeneity in preferences for renewable home heating systems among Irish households. *Applied Energy, 307, 118219.* https://doi.org/10.1016/j.apenergy.2021.118219

Meyerhoff, J., Oehlmann, M., Weller, P., 2015. The influence of design dimensions on stated choices in an environmental context. *Environmental and Resource Economics, 61, 385-407.* https://doi.org/10.1007/s10640-014-9797-5

Miettinen, T., Kosfeld, M., Fehr, E., Weibull, J.W., 2020. Revealed Preferences in a Sequential Prisoners' Dilemma: A Horse-Race Between Six Utility Functions. *Journal of Economic Behaviour & Organization, 173, C, 1-25.* https://doi.org/10.1016/j.jebo.2020.02.018

Mining Remediation Authority, 2024. X, 15 October 2024. https://x.com/MiningRemAuth/status/1846148923783630932

Mirrlees, J.A., 1975) Optimal Commodity Taxation in a Two-Class Economy. *Journal of Public Economics, 4, 1, 27-33.* https://doi.org/10.1016/0047-2727(75)90021-3

Molloy, P. (2019). Run on Less with Hydrogen Fuel Cells. *RMI.* https://rmi.org/run-on-less-with-hydrogen-fuel-cells/ *Last visited: 03/12/2024.*

Morey, E.R., 1981. The demand for site-specific recreational activities: a characteristics approach. *Journal of Environmental Economics and Management, 8, 4, 345-371.* https://doi.org/10.1016/0095-0696(81)90046-2

Morningstar Indexes and Morningstar Sustainalytics, 2023. Voice of the Asset Owner Survey 2023. Quantitative Analysis. *Kuh, T., Gast, A. https://assets.contentstack.io/v3/assets/bltabf2a7413d5a8f05/blt933cb07c08fa9f1d/6553b26c0e64b99bd46ecbaf/Voice-of-the-Asset-Owner-Survey-2023-Quant-Analysis.pdf Last accessed: 23/01/2024*

Myles, G., 1995. Public Economics. *Cambridge: Cambridge University Press.* https://doi.org/10.1017/CBO9781139170949

Naga, L., Marsiliani, L., Renström, T., 2024. Kantian Morality and Optimal Second-Best Commodity Taxation. *Working Paper.*

National Infrastructure Commission, 2023. Technical annex: hydrogen heating. https://nic.org.uk/app/uploads/NIA-2-Technical-annex-hydrogen-heating-Final-18-October-2023.pdf Last accessed: 03/12/2024

New International Version. (2011). BibleGateway.com. https://www.biblegateway.com/passage/?search=Matthew%207%3A12&version=NIV

Northern Mine Research Society. http://nmrs.org.uk/mines-map/coal-mining-in-the-british-isles/collieries-of-the-british-isles/coal-mines-england/ *Last accessed: 21/11/2024*

Nyborg, K., 2018. Social Norms and the Environment. *Annual Review of Resource Economics, 10, 1, 405-423.* https://doi.org/10.1146/annurev-resource-100517-023232

Nyborg, K., 2019. Social norms and the environment. *Annual Reviews Resource Economics, 10, 405-423.* https://doi.org/10.1146/annurev-resource-100517-023232

Nyborg, K., 2020. No Man is an Island: Social Coordination and the Environment. *Environmental and Resource Economics, 76, 1, 177-193.* https://doi.org/10.1007/s10640-020-00415-2

Odeh, N., Hill, N., and Forster, D., 2013. Current and Future Lifecycle Emissions of Key 'Low Carbon' Technologies and Alternatives. *Ricardo-AEA, technical report. https://www.theccc.org.uk/wp-content/uploads/2013/04/Ricardo-AEA-lifecycle-emissions-low-carbon-technologies-April-2013.pdf Last visited: 03/12/2024*

Ofgem (a) Average gas and electricity usage. https://www.ofgem.gov.uk/average-gas-and-electricity-usage#:~:text=We%20estimate%20the%20typical%20household,of%20gas%20in%20a%20year. Last visited: 03/12/2024

Ofgem (b). Energy Price Cap. https://www.ofgem.gov.uk/energy-price-cap Last visited: 03/12/2024

OnePlanetCapital, 2022. https://www.unbiased.co.uk/news/financial-adviser/socially-responsible-investing-predicted-to-double-in-2021. Last visited: 30/03/2022

ONS Opinions and Lifestyle Survey, July 2024. Public opinions and social trends, Great Britain. https://www.ons.gov.uk/peoplepopulationandcommunity/wellbeing/bulletins/publicopinionsandsocialtrendsgreatbritain/july2024 *Last visited: 21/08//2024*

Ottman, J.A., 1992. Industry's Response to Green Consumerism. *Journal of Business Strategy, 13, 4, 3-7.* https://doi.org/10.1108/eb039498

Parkinson, B., Balcombe, P., Speirs, J. F., Hawkes, A. D., and Hellgardt, K., 2019. Levelized cost of CO2 mitigation from hydrogen production routes. *Energy and Environmental Science, 12, 1, 19–40.* https://doi.org/10.1039/C8EE02079E

Parliamentary Office of Science & Technology, 2016. Carbon Footprint of Heat Generation. Technical report. *Houses of Parliament, POSTNOTE, 523.* https://researchbriefings.files.parliament.uk/documents/POST-PN-0523/POST-PN-0523.pdf

Pástor, L., Stambaugh, R.F., Taylor, L.A., 2021. Sustainable Investing in Equilibrium. *Journal of Financial Economics, 142, 2, 550-571.* https://doi.org/10.1016/j.jfineco.2020.12.011

Pástor, L., Vorsatz, M.B., 2020. Mutual Fund Performance and Flows during the COVID-19 Crisis. *Review of Asset Pricing Studies, 10, 4, 791-833.* https://doi.org/10.1093/rapstu/raaa015

Petrovich, B., Hille, S.L., Wüstenhagen, R., 2019. Beauty and the Budget: A segmentation study of residential solar adopters. *Ecological Economics, 164, 106353.* https://doi.org/10.1016/j.ecolecon.2019.106353

Pillsburg, W.B., 1934. The unit of experience. *The fundamentals of psychology, editor W.B. Pillsbury, 3rd edition, MacMillan Co., 388-407.*

Posit team, 2024. RStudio: Integrated Development Environment for R. *Posit Software, PBC, Boston, MA*. http://www.posit.co/.

Ramsey, F.P., 1927. A Contribution to the Theory of Taxation. *The Economic Journal, 37, 145, 47-61.* https://doi.org/10.2307/2222721

Rege, M., 2004. Social Norms and Private Provision of Public Goods. *Journal of Public Economic Theory, 6, 1, 65-77.* https://doi.org/10.1111/j.1467-9779.2004.00157.x

Remeha. Green pilot projects with 100% H2 boilers in building environment. https://northsearegion.eu/media/23618/raymond-van-de-tempel-remeha.pdf Last accessed: 09/12/2024

Renneboog, L., Horst, J.T., Zhang, C., 2008. Socially Responsible Investments: Institutional Aspects, Performance, and Investor Behaviour. *Journal of Banking & Finance, 32, 1723-1742.* https://doi.org/10.1016/j.jbankfin.2007.12.039

Renström, T.I., Spararo, L., Marsiliani, L., 2019. Optimal Taxation, environmental quality, socially responsible firms and investors. *International Review of Environmental and Resource Economics,* 13, 3-4, 339-373. https://doi.org/10.1561/101.00000112

Renström, T.I., Spararo, L., Marsiliani, L., 2021. Can Subsidies rather than Pollution Taxes Break the Trade-off between Economic Output and Environmental Protection? *Energy Economics*, 95, 105084. https://doi.org/10.1016/j.eneco.2020.105084

Reuters, 2021. Kerber, R., Jessop, S., Analysis: How 2021 became the year of ESG investing. Reuters. https://www.reuters.com/markets/us/how-2021-became-year-esg-investing-2021-12-23/

Revelt, D., Kenneth, T., 1998. Mixed logit with repeated choices: households' choices of appliance efficiency level. *Review of Economics and Statistics, 80, 1-11.* https://doi.org/10.1162/003465398557735

Roemer, J.E., 2010. Kantian Equilibrium. *The Scandinavian Journal of Economics, 11, 1, 1-24.* https://doi.org/10.1 1 1 1/j. 1467-9442.2009.0 1592.x

Roemer, J.E., 2015. Kantian Optimisation in the Presence of Externalities. *Journal of Public Economics,* The Nordic Model, 127, 45-57. https://doi.org/10.1016/j.jpubeco.2014.03.011

Roemer, J.E., 2019. How we cooperate: a theory of Kantian optimisation. *Yale University Press.* *https://doi.org/10.2307/j.ctvfc52jk*

Sadka, E., 1978. On the Optimal Taxation of Consumption Externalities. *The Quarterly Journal of Economics, 92, 1, 165-174.* https://doi.org/10.2307/1886003

Samuelson, P.A., 1952. Economic Theory and Mathematics—An Appraisal. *The American Economic Review, 42, 2, 56-66.* https://www.jstor.org/stable/1910585

Sandmo, A., 1975. Optimal Taxation in the Presence of Externalities. *The Swedish Journal of Economics, 77, 1, 86-98.* https://doi.org/10.2307/3439329

Sandor, Z., Wedel, M., 2001. Designing Conjoint Choice Experiments using Managers' Prior Beliefs. *Journal of Marketing Research, 38, 4.* https://doi.org/10.1509/jmkr.38.4.430.18904

Sarrias, M., 2020. Individual-specific posterior distributions from mixed logit models: properties, limitations and diagnostic checks. *Journal of Choice Modelling, 36, 100224.* https://doi.org/10.1016/j.jocm.2020.100224

Scarpa, R., Notaro, S., Louviere, J., Raffaelli, R., 2011. Exploring Scale Effects of Best/Worst Rank Ordered Choice Data to Estimate Benefits of Tourism in Alpine Grazing Common. *American Journal of Agricultural Economics, 93, 3, 813-828.* https://doi.org/10.1093/ajae/aaq174

Scarpa, R., Rose, J.M., 2008. Design efficiency for non-market valuation with choice modelling: how to measure it, what to report and why. *Australian Journal of Agricultural and Resource Economics, Australian Agricultural and Rsource Economics Society, 52, 3, 253-282.* https://doi.org/10.22004/ag.econ.118543

Scarpa, R., Willis, K., 2010. Willingness-to-pay for renewable energy: Primary and discretionary choice of British households for micro-generation technologies. *Energy Economics, 32, 129-136.* https://doi.org/10.1016/j.eneco.2009.06.004

Scholfield, W. (2024). Electric boilers vs. gas boilers: the pros & cons of each. *Boxt.* https://www.boxt.co.uk/boilers/guides/electric-boilers-vs-gas-boilers-the-pros-cons-of-each *Last visited: 03/12/2024*

Schwartz, S.H., 1977. Normative Influences on Altruism. *Advances in Experimental Social Psychology, Editor Leonard Berkowitz,* New York: Academic Press, 221-279. http://dx.doi.org/10.1016/s0065-2601(08)60358-5

Sen, A. K. 1977. 'Rational Fools: A Critique of the Behavioural Foundations of Economic Theory'. *Philosophy & Public Affairs* 6, 4, 317–44. https://www.jstor.org/stable/2264946

Smith, A. 1759. Introduction to the Theory of Moral Sentiments. *Ed. Haakonssen, K., Cambridge University Press, 2012*. https://doi-org.ezphost.dur.ac.uk/10.1017/CBO9780511800153

Sottile, E., Meloni, I., Cherchi, E., 2015. A Hybrid discrete choice model to assess the effect of awareness and attitude towards environmentally friendly travel modes. *Transportation Research Procedia, 5, 44-55.* https://doi.org/10.1016/j.trpro.2015.01.017

Statistica, 2024. Electricity consumption by households in the United Kingdom (UK) from 2000 to 2023. https://www.statista.com/statistics/323410/domestic-electricity-volumes-in-the-united-kingdom-uk/ Last visited: 23/10/2024.

Stern, P.C., Dietz, T., Able, T., Guagnano, G.A., Kalof, L., 1999. A Value Belief Norm Theory of Support for Social Movements: the case of environmentalism. *Human Ecology Review, 6, 81-97.* https://cedar.wwu.edu/hcop_facpubs/1

Stern, P.C., Kalof, L., Dietz, T., Guagnano, G.A., 1995. Values, beliefs and Proenvironmental Action: attitude formation toward emergent attitude objects. *Journal of Applied Social Psychology, 25, 18, 1611-1636.* https://doi.org/10.1111/j.1559-1816.1995.tb02636.x

Strazzera, E., Mura, M., Contu, D., 2012. Combining choice experiments with psychometric scales to assess the social acceptability of wind energy projects: a latent class approach. *Energy Policy, 48, 334-347.* https://doi.org/10.1016/j.enpol.2012.05.037

Steet, D.J., Bunch, D.S., Moore, B., 2001. Optimal Designs for 2^k paired comparison experiments. *Communications in Statistics, Theory and Methods, 30, 2149-2171.* https://doi.org/10.1081/STA-100106068

Street, D.J., Burgess, L., Louviere, J.J., 2005. Quick and easy choice sets: constructing optimal and nearly optimal stated choice experiments. *International Journal of Research in Marketing, 22, 4, 459-470.* https://doi.org/10.1016/j.ijresmar.2005.09.003

Taye, F.A., Vedel, S.V., Jacobsen, J.B., 2018. Accounting for environmental attitude to explain variations in willingness to pay for forest ecosystem services using the new environmental paradigm. *Journal of Environmental Economics and Policy, 7, 4, 420-440.* https://doi.org/10.1080/21606544.2018.1467346

Temme, D., Paulssen, M., Dannewald, T., 2007. Integrating latent variables in discrete choice models: how higher-order values and attitudes determine consumer choice. *SFB 649 Discussion Paper, No. 2007,065, Humboldt University of Berlin, Collaborative Research Center 649- Economic Risk, Berlin.* https://hdl.handle.net/10419/25237

The Coal Authority (2022). Delivering mine water heat as a strategic resource in Great Britain-March 2022 *Making a better future for people and the environment in mining areas Coalfield areas in Great Britain. Technical report.* https://www.drkieranmullan.org.uk/sites/www.drkieranmullan.org.uk/files/2023-06/Appendix%201%20Delivering%20mine%20water%20heat%20as%20a%20strategic%20resource%20in%20Great%20Britain%20–%20March%202022.pdf *Last visited: 03/12/2024*

The Engineer (2021). Big Four make price promise on domestic hydrogen boilers. https://www.theengineer.co.uk/content/news/big-four-make-price-promise-on-domestic-hydrogen-boilers/ Last visited: 03/12/2024

Thiene, M., Scarpa, R., 2009. Deriving and testing efficient estimates of WTP distributions in destination choice models. *Environmental and Resource Economics, 44, 379-395.* https://doi.org/10.1007/s10640-009-9291-7

Train, K., 1998. Recreation Demand Models with Taste Differences over People. *Land Economics, 74, 2, 230-239.* https://doi.org/10.2307/3147053

Train, K., 1999. Halton Sequences for Mixed Logit. *Department of Economics, University of California, Berkley.* https://escholarship.org/uc/item/6zs694tp

Train, K., McFadden, D., Goett, A., 1987. Consumer Attitudes and Voluntary Rate Schedules for Public Utilities. *Review of Economics and Statistics, 69, 383-391.* https://doi.org/10.2307/1925525

Train, K.E., 2009. Discrete choice models with simulation. *Cambridge University Press, Cambridge.* https://doi.org/10.1017/CBO9780511805271

Turner, J.C., Brown, R.J., Tajfel, H., 1979. Social comparison and group interest in ingroup favouritism. *European Journal of Social Psychology. 9, 2, 187-204.* https://doi.org/10.1002/ejsp.2420090207

Udalov, V., Perret, J., Vasseur, V., 2017. Environmental motivations behind individuals' energy efficiency investments and daily energy-saving behaviour: evidence from Germany, the Netherlands and Belgium. *International Economics and Economic Policy, 14, 3, 1-19.* https://doi.org/10.1007/s10368-017-0381-7

UK Parliament, Mine Closures, Volume 255: debated on Tuesday 21 February 1995. https://hansard.parliament.uk/Commons/1995-02-21/debates/3cb5bc10-8169-4dd9-8b1b-dcd63fb62751/MineClosures Last visited: 09/10/2024

Van Leeuwen, B., Alger, I., 2021. Estimating Social Preferences and Kantian Morality in Strategic Interactions. 19-100, *IAST Working Papers, Institute for Advanced Study in Toulouse (IAST).* https://www.tse-fr.eu/sites/default/files/TSE/documents/doc/wp/2019/wp_tse_1056.pdf

Vecchiato, D., Tempesta, T., 2015. Public preferences for electricity contracts including renewable energy: a marketing analysis with choice experiments. *Energy, 88, 168-179.* https://doi.org/10.1016/j.energy.2015.04.036

Vij, A., Walker, J.L., 2016. How, when and why integrated choice and latent variable models are latently useful. *Transportation Research Part B, 90, 192-217.* https://doi.org/10.1016/j.trb.2016.04.021

WDS Green Energy. Air Source Heat Pump Technology. https://www.wdsgreenenergy.co.uk/air-source-heat-pump-technology/ Last accessed: 09/12/2024

Westaby, J.D., 2005. Behavioural Reasoning Theory: identifying new linkages underlying intentions and behaviour. *Organisational Behaviour and Human Decision Making Processes, 98, 2, 97-120.* https://doi.org/10.1016/j.obhdp.2005.07.003

Willis, K., Scarpa, R., Gilroy, R., Hamza, N., 2011. Renewable energy adoption in ageing population: Heterogeneity in preference for micro-generation technology adoption. *Energy Policy, 39, 10, 6021-6029.* https://doi.org/10.1016/j.enpol.2011.06.066

Zerbib, O.D., 2019. The Effect of Pro-Environmental Preferences on Bond Prices: Evidence from Green Bonds. *Journal of Banking and Finance, 98, 39-60.* https://doi.org/10.1016/j.jbankfin.2018.10.012

Zivin, J.G., Small, A., 2005. The Modigliani-Miller Theory of Altruistic Corporate Social Responsibility. *Topics in Economic Analysis & Policy,* 5, 1, 10. https://doi.org/10.1515/1538-0653.1369

Zorić, J., Hrovatin, N., 2012. Household willingness to pay for green electricity in Slovenia. *Energy Policy, 47, 180-187.* https://doi.org/10.1016/j.enpol.2012.04.055

Appendix A: Appendix for Chapter 1

Appendix A1: Derivation of Demand Elasticities

First, consider the dirty good.

$$\varepsilon_Z = \frac{\partial Z}{\partial q_z}\frac{q_z}{Z} = \frac{q_z}{Z}\sum_{h=1}^{H}\frac{\partial z^h}{\partial q_z} \qquad (A1.1)$$

Consider the moral consumer demand for the dirty good as in equation 1.11, $z^h = \frac{(1-\phi'(Z)Z)(w^h+I^h)}{(1+\theta^h+\eta^h-\phi'(Z)Z)q_z}$, differentiate this with respect to the price of the dirty good.

$$\frac{\partial z^h}{\partial q_z} = \left(-\frac{\phi''(Z)Z+\phi'(Z)}{1-\phi'(Z)Z}\frac{\partial Z}{\partial q_z} + \frac{\phi''(Z)Z+\phi'(Z)}{1+\theta^h+\eta^h-\phi'(Z)Z}\frac{\partial Z}{\partial q_z} - \frac{1}{q_z}\right)z^h$$

$$= -\frac{(\theta^h+\eta^h)(\phi''(Z)Z+\phi'(Z))z^h}{(1-\phi'(Z)Z)(1+\theta^h+\eta^h-\phi'(Z)Z)}\frac{\partial Z}{\partial q_z} - \frac{z^h}{q_z}$$

$$= -\frac{m^h z^h}{Z}\frac{\partial Z}{\partial q_z} - \frac{z^h}{q_z} \qquad (A1.2)$$

We then aggregate this over all households to obtain the aggregate demand elasticity.

$$\frac{\partial Z}{\partial q_z} = -\frac{\partial Z}{\partial q_z}\frac{\sum_{h=1}^{H} m^h z^h}{Z} - \frac{Z}{q_z} \qquad (A1.3)$$

This can be rearranged to obtain the price elasticity of demand.

$$\varepsilon_Z = \frac{\partial Z}{\partial q_z}\frac{q_z}{Z} = -\frac{1}{1+\frac{\sum_{h=1}^{H} m^h z^h}{Z}} \qquad (A1.4)$$

We can then repeat this process for the clean good, using the clean good demand from equation 1.12, $x^h = \frac{\theta^h(w^h+I^h)}{(1+\theta^h+\eta^h-\phi'(Z)Z)q_x}$. This gives,

$$\varepsilon_x = \frac{\partial X}{\partial q_x}\frac{q_x}{X} = -1$$

Using the different assumptions across the four different versions of the model, we can work out the different demand elasticities.

Table A1: Price elasticity of demand across different versions of the model

	Homogeneous	Heterogeneous
Non-moral	$\varepsilon_Z = -1, \varepsilon_x = -1$	$\varepsilon_Z = -1, \varepsilon_x = -1$
Moral	$\varepsilon_Z = -\frac{1}{1+m}, \varepsilon_x = -1$	$\varepsilon_Z = -\frac{1}{1+\frac{\sum_{h=1}^{H} m^h z^h}{Z}}, \varepsilon_x = -1$

Appendix A2: Equivalence of Utility Maximisation and Cost Minimisation

Compensated demand is the outcome of the dual cost-minimisation problem, it shows how demand would change as a result of a change in the price, compensating to remain at the same utility level. To employ the Slutsky decomposition, it is important to demonstrate that the dual cost minimisation is consistent with the utility maximisation carried out in the paper.

This problem can be set out as consumers choosing their consumption and leisure to minimise their expenditure subject to achieving a given level of utility. Given the Kantian optimisation, it may be interpreted as achieving a given level of moral utility or 'rightness' at the smallest cost.

$$\mathrm{Min}_{z^h, x^h, (1-l^h)} q_z z^h + q_x x^h - w^h l^h \tag{A2.1}$$

subject to

$$\ln(z^h) + \theta^h \ln(x^h) + \eta^h \ln(1 - l^h) = u^h + \phi(Z) \tag{A2.2}$$

Construct the Lagrangian,

$$\mathcal{L} = q_z \gamma z^h + q_x x^h - w l^h + \beta^h \{\ln(\gamma z^h) + \theta^h \ln(x^h) + \eta^h \ln(1 - l^h) - \phi(\gamma Z) - u^h\} \tag{A2.3}$$

The first order conditions would give,

$$\left.\frac{\partial \mathcal{L}}{\partial \gamma}\right|_{\gamma=1} = q_z z^h + \beta^h \{1 - \phi'(Z) Z\} = 0$$

$$z^{h,c} = -\frac{\beta^h}{q_z}(1 - \phi'(Z)Z) \qquad (A2.4)$$

$$\frac{\partial \mathcal{L}}{\partial x^h} = q_x + \beta^h \left\{\frac{\theta^h}{x^h}\right\} = 0$$

$$x^{h,c} = -\frac{\beta^h}{q_x}\theta^h \qquad (A2.5)$$

$$\frac{\partial \mathcal{L}}{\partial l^h} = -w^h + \beta^h \left\{-\frac{\eta^h}{1 - l^h}\right) = 0$$

$$\left(1 - l^{h,c}\right) = -\frac{\beta^h}{w^h}\eta^h \qquad (A2.6)$$

Substituting these into the constraint gives,

$$\ln\left(-\frac{\beta^h}{q_z}(1 - \phi'(Z)Z)\right) + \theta^h \ln\left(-\frac{\beta^h}{q_x}\theta^h\right) + \eta^h \ln\left(-\frac{\beta^h}{w^h}\eta^h\right) - \left(u^h + \phi(Z)\right) = 0 \qquad (A2.7)$$

When utility, u^h, is set at the same level as in the utility maximisation problem (equation 1.14), we find that,

$$\beta^h = -\frac{\left(w + I^h\right)}{(1 + \theta + \eta - \phi'(Z)Z)} = -\frac{1}{\alpha^h} \qquad (A2.8)$$

When β^h is substituted into the first order conditions (equations A2.4 to A2.6), this results in demands for $z^h, x^h,$ and $\left(1 - l^h\right)$ which are equivalent to the utility maximisation problem.

Appendix A3: Compensated Demands and Proof of the Symmetry of Substitution Effects

Appendix A3.1 Compensated Demands

To calculate the Hicksian compensated demands for the dirty good and the clean good we can carry out the dual moral cost minimisation problem, as in Appendix A2. From equation A2.7 we can adopt a general expression for β^h,

$$-\beta^h = \left[\frac{q_z q_x^{\theta^h} w^{h^{\eta^h}} e^{\phi(Z)+u^h}}{(1-\phi'(Z)Z)\theta^{h^{\theta^h}} \eta^{h^{\eta^h}}}\right]^{\frac{1}{1+\theta^h+\eta^h}}. \qquad (A3.1)$$

Equation A3.1 can then be substituted into the first-order conditions from the dual cost minimisation (equations A2.4 to A2.6) to obtain the moral Hicksian compensated demands for the dirty good and the clean good.

$$\begin{aligned} z^{h,c} &= \left[\frac{q_z q_x^{\theta^h} w^{h^{\eta^h}} e^{\phi(Z)+u^h}}{(1-\phi'(Z)Z)\theta^{h^{\theta^h}} \eta^{h^{\eta^h}}}\right]^{\frac{1}{1+\theta^h+\eta^h}} \frac{(1-\phi'(Z^c)Z^c)}{q_z} \\ &= \left[\frac{q_z^{-(\theta^h+\eta^h)} q_x^{\theta^h} w^{h^{\eta^h}} e^{\phi(Z^c)+u^h}}{(1-\phi'(Z^c)Z^c)^{-(\theta^h+\eta^h)}\theta^{h^{\theta^h}} \eta^{h^{\eta^h}}}\right]^{\frac{1}{1+\theta^h+\eta^h}}, \end{aligned} \qquad (A3.2)$$

$$x^{h,c} = \left[\frac{q_z q_x^{\theta^h} w^{h^{\eta^h}} e^{\phi(Z)+u^h}}{(1-\phi'(Z)Z)\theta^{h^{\theta^h}} \eta^{h^{\eta^h}}}\right]^{\frac{1}{1+\theta^h+\eta^h}} \frac{\theta^h}{q_x} = \left[\frac{q_z q_x^{-(1+\eta^h)} w^{h^{\eta^h}} e^{\phi(Z^c)+u^h}}{(1-\phi'(Z^c)Z^c)\theta^{h^{-(1+\eta^h)}} \eta^{h^{\eta^h}}}\right]^{\frac{1}{1+\theta^h+\eta^h}}. (A3.3)$$

<u>Appendix A3.2 Proof of Slutsky Substitution Symmetry</u>

Symmetry of the Slutsky substitution effects requires that,

$$\frac{dZ^c}{dq_x} = \frac{dX^c}{dq_z}. \qquad (A3.4)$$

This can be investigated by checking whether the change in aggregate compensated demand for the dirty good, $Z^c = \sum_{h=1}^{H} z^{h,c}$, when there is a change in the price of the clean good is equal to the change in aggregate compensated demand for the clean good, $X^c = \sum_{h=1}^{H} x^{h,c}$, when there is a change in the price of the dirty good.

Starting with the dirty good, we can take the individual compensated demands from equation A3.2, take logs, differentiate with respect to the price of the clean good, and then sum across all households.

$$\frac{\partial Z^c}{\partial q_x} = \sum_{h=1}^{H} \frac{\partial z^{h,c}}{\partial q_x}$$

$$= \sum_{h=1}^{H} \frac{\theta^h z^{h,c}}{(1+\theta^h+\eta^h)q_x} + \frac{\phi'(Z^c) z^{h,c}}{1+\theta^h+\eta^h} \frac{\partial Z^c}{\partial q_x} - \frac{(\theta^h+\eta^h)\big(\phi''(Z^c)Z^c+\phi'(Z^c)\big)z^{h,c}}{(1+\theta^h+\eta^h)(1-\phi'(Z^c)Z^c)} \frac{\partial Z^c}{\partial q_x} \qquad (A3.5)$$

Rearrange to give,

$$\frac{\partial Z^c}{\partial q_x} = \frac{\frac{1}{q_x}\sum_{h=1}^{H} \frac{\theta^h z^{h,c}}{1+\theta^h+\eta^h}}{1-\phi'(Z^c)\sum_{h=1}^{H} \frac{z^{h,c}}{1+\theta^h+\eta^h} + \frac{\phi''(Z^c)Z^c+\phi'(Z^c)}{1-\phi'(Z^c)Z^c}\sum_{h=1}^{H} \frac{(\theta^h+\eta^h)z^{h,c}}{1+\theta^h+\eta^h}} \qquad (A3.6)$$

Repeat this process with the aggregate compensated demand for the clean good.

$$\frac{\partial X^c}{\partial q_z} = \sum_{h=1}^{H} \frac{\partial x^{h,c}}{\partial q_z}$$

$$= \frac{1}{q_z}\sum_{h=1}^{H} \frac{x^{h,c}}{(1+\theta^h+\eta^h)} + \frac{\partial Z^c}{\partial q_z}\sum_{h=1}^{H} x^{h,c}\left(\frac{\phi'(Z^c)}{1+\theta^h+\eta^h} + \frac{\phi''(Z^c)Z^c+\phi'(Z^c)}{(1+\theta^h+\eta^h)(1-\phi'(Z^c)Z^c)}\right) \qquad (A3.7)$$

To simplify the expression in equation A3.7, we need to separately calculate $\frac{\partial Z^c}{\partial q_z}$ using the compensated demand for the dirty good and partially differentiating it with respect to its own price.

$$\frac{\partial Z^c}{\partial q_z} = \frac{-\frac{1}{q_z}\sum_{h=1}^{H} \frac{(\theta^h+\eta^h)z^{h,c}}{1+\theta^h+\eta^h}}{1-\phi'(Z^c)\sum_{h=1}^{H} \frac{z^{h,c}}{1+\theta^h+\eta^h} + \frac{\phi''(Z^c)Z^c+\phi'(Z^c)}{1-\phi'(Z^c)Z^c}\sum_{h=1}^{H} \frac{(\theta^h+\eta^h)z^{h,c}}{1+\theta^h+\eta^h}} \qquad (A3.8)$$

Substitute the expression in equation A3.8 back into equation A3.7,

$$\frac{\partial X^c}{\partial q_z}$$

$$= \frac{1}{q_z}\sum_{h=1}^{H} \frac{x^{h,c}}{(1+\theta^h+\eta^h)}$$

$$- \frac{-\frac{1}{q_z}\sum_{h=1}^{H} \frac{(\theta^h+\eta^h)z^{h,c}}{1+\theta^h+\eta^h}\left(\phi'(Z^c)\sum_{h=1}^{H} \frac{x^{h,c}}{1+\theta^h+\eta^h} + \frac{\phi''(Z^c)Z^c+\phi'(Z^c)}{1-\phi'^{(Z^c)Z^c}}\sum_{h=1}^{H} \frac{x^{h,c}}{1+\theta^h+\eta^h}\right)}{1-\phi'(Z^c)\sum_{h=1}^{H} \frac{z^{h,c}}{1+\theta^h+\eta^h} + \frac{\phi''(Z^c)Z^c+\phi'(Z^c)}{1-\phi'(Z^c)Z^c}\sum_{h=1}^{H} \frac{(\theta^h+\eta^h)z^{h,c}}{1+\theta^h+\eta^h}}$$

$$\frac{\partial X^c}{\partial q_z} = \frac{\left(\frac{1-\phi'(Z^c)Z^c}{q_z}\sum_{h=1}^{H}\frac{x^{h,c}}{1+\theta^h+\eta^h}\right)}{1-\phi'(Z^c)\sum_{h=1}^{H}\frac{z^{h,c}}{1+\theta^h+\eta^h}+\frac{\phi''(Z^c)Z^c+\phi'(Z^c)}{1-\phi'(Z^c)Z^c}\sum_{h=1}^{H}\frac{(\theta^h+\eta^h)z^{h,c}}{1+\theta^h+\eta^h}} \qquad (A3.9)$$

To investigate the equivalence of the Slutsky substitution effects, we can use the compensated demand functions to obtain $z^{h,c}$ in terms of $x^{h,c}$, such that $z^{h,c} = \frac{(1-\phi'(Z^c)Z^c)q_x x^{h,c}}{\theta^h q_z}$. Substituting this into equation A3.6 gives,

$$\frac{\partial Z^c}{\partial q_x} = \frac{\frac{(1-\phi'(Z^c)Z^c)}{q_z}\sum_{h=1}^{H}\frac{x^{h,c}}{1+\theta^h+\eta^h}}{1-\phi'(Z^c)\sum_{h=1}^{H}\frac{z^{h,c}}{1+\theta^h+\eta^h}+\frac{\phi''(Z^c)Z^c+\phi'(Z^c)}{1-\phi'(Z^c)Z^c}\sum_{h=1}^{H}\frac{(\theta^h+\eta^h)z^{h,c}}{1+\theta^h+\eta^h}} \qquad (A3.10)$$

The right-hand side of equation A3.10 is equivalent to the right-hand side of equation A3.9, proving that in the case of moral households, the Slutsky substitution effects are symmetric (i.e. equation A3.4 holds).

Appendix A4: Heterogeneous pollution damages

Households may suffer different marginal damages from pollution. A straightforward way of introducing heterogeneity is to introduce an additional household-specific parameter as a multiplier on the damage function, this assumes that the shape of the damage function is homogeneous, but the scale differs. Solving the model with heterogeneous damages results in agents who suffer the highest pollution damages reducing their own dirty good consumption by larger amounts. The overall effect will depend upon how pollution damages relate to clean good preference, leisure preference and income levels. On the whole, the same aggregate results hold, yet those who suffer more from pollution bear a relatively greater burden in terms of correcting pollution externalities.

$$L^h = \ln(\gamma^h z^h) + \theta^h \ln(x^h) + \eta^h \ln(1-l^h) - \psi^h \phi(\gamma^h Z) + \alpha^h(I^h + w^h l^h - q_z\gamma^h z^h - q_x x^h) \qquad (A4.1)$$

Derive first order conditions.

$$\left.\frac{\partial L^h}{\partial \gamma^h}\right|_{\gamma^h=1} = 1 - \psi^h\phi'(Z)Z - \alpha^h q_z z^h = 0 \qquad (A4.2)$$

$$z^h = \frac{1-\psi^h\phi'(Z)Z}{\alpha^h q_z} \qquad (A4.3)$$

$$x^h = \frac{\theta^h}{\alpha^h q_x} \tag{A4.4}$$

$$\left(1 - l^h\right) = \frac{\eta^h}{\alpha^h w^h} \tag{A4.5}$$

Substitute first order conditions into budget constraint to obtain expression for α^h:

$$\alpha^h = \frac{1 + \theta^h + \eta^h - \psi^h \phi'(Z)Z}{I^h + w^h} \tag{A4.6}$$

Substitute α^h into first order conditions to obtain expressions for the Marshallian demands:

$$z^h = \frac{\left(1 - \psi^h \phi'(Z)Z\right)\left(I^h + w^h\right)}{(1 + \theta^h + \eta^h - \psi^h \phi'(Z)Z)q_z} \tag{A4.7}$$

$$x^h = \frac{\theta^h\left(I^h + w^h\right)}{(1 + \theta^h + \eta^h - \psi^h \phi'(Z)Z)q_x} \tag{A4.8}$$

$$\left(1 - l^h\right) = \frac{\eta^h\left(I^h + w^h\right)}{(1 + \theta^h + \eta^h - \psi^h \phi'(Z)Z)w^h} \tag{A4.9}$$

Indirect utility function then becomes:

$$\begin{aligned} V^h = ln\left(\frac{\left(1 - \psi^h \phi'(Z)Z\right)\left(I^h + w^h\right)}{(1 + \theta^h + \eta^h - \psi^h \phi'(Z)Z)q_z}\right) + \theta^h\, ln \frac{\theta^h\left(I^h + w^h\right)}{(1 + \theta^h + \eta^h - \psi^h \phi'(Z)Z)q_x} \\ + \eta^h\, ln \frac{\eta^h\left(I^h + w^h\right)}{(1 + \theta^h + \eta^h - \psi^h \phi'(Z)Z)w^h} - \psi^h \phi(Z) \end{aligned} \tag{A4.10}$$

Differentiate indirect utility function with respect to price of each goods to see how demand responds to a change in the tax rate.

$$\begin{aligned} V^h = ln\left(1 - \psi^h \phi'(Z)Z\right) + \left(1 + \theta^h + \eta^h\right) ln\left(I^h + w^h\right) \\ -\left(1 + \theta^h + \eta^h\right) ln\left(1 + \theta^h + \eta^h - \psi^h \phi'(Z)Z\right) - ln(q_z) \\ - ln(q_x) - ln\left(w^h\right) + \theta^h\, ln\, \theta^h + \eta^h\, ln\, \eta^h - \psi^h \phi(Z) \end{aligned} \tag{A4.11}$$

$$\frac{\partial V^h}{\partial q_z} = -\frac{1}{q_z} - \left[1 + \frac{(\theta^h + \eta^h)\psi^h\big(\phi''(Z)Z + \phi'(Z)\big)Z}{(1 + \theta^h + \eta^h - \psi^h\phi'(Z)Z)(1 - \psi^h\phi'(Z)Z)}\right]\psi^h\phi'(Z)\frac{\partial Z}{\partial q_z} \qquad (A4.12)$$

$$\frac{\partial V^h}{\partial q_z} = -\frac{1}{q_z} - \psi^h\phi'(Z)\big(1 + m^h\big)\frac{\partial Z}{\partial q_z} \qquad (A4.13)$$

Where $m^h = \frac{(\theta^h+\eta^h)\psi^h\left(\phi''(Z)Z+\phi'(Z)\right)Z}{(1+\theta^h+\eta^h-\psi^h\phi'(Z)Z)(1-\psi^h\phi'(Z)Z)}$.

Meanwhile,

$$\frac{\partial V^h}{\partial q_x} = -\frac{\theta^h}{q_x} \qquad (A4.14)$$

Within the government problem, we then have equation 1.18 become:

$$\frac{\partial L}{\partial q_z} = \sum_{h=1}^{H}\frac{\partial W}{\partial V^h}\left(-\frac{1}{q_z} - \psi^h\phi'(Z)\big(1 + m^h\big)\frac{\partial Z}{\partial q_z}\right) + \lambda\left(Z + (q_z - p_z)\frac{\partial Z}{\partial q_z} + (q_x - p_x)\frac{\partial X}{\partial q_z}\right) = 0 \; (A4.15)$$

Leading to 1.21 and 1.22 becoming

$$\frac{\Delta Z^c}{Z} = \frac{1}{\lambda}\sum_{h=1}^{H}\frac{\partial W}{\partial V^h}\left(\frac{1}{q_z} + \psi^h\phi'(Z)\big(1 + m^h\big)\frac{\partial Z}{\partial q_z}\right)\frac{1}{Z} - 1 + t_z\frac{\partial Z}{\partial \bar{I}} + t_x\frac{\partial X}{\partial \bar{I}} \qquad (A4.16)$$

$$\frac{\Delta X^c}{X} = \frac{1}{\lambda}\sum_{h=1}^{H}\frac{\partial W}{\partial V^h}\frac{\theta^h}{q_x}\frac{1}{X} - 1 + t_z\frac{\partial Z}{\partial \bar{I}} + t_x\frac{\partial X}{\partial \bar{I}} \qquad (A4.17)$$

Thus 1.23 would be:

$$\frac{\Delta Z^c}{Z} - \frac{\Delta X^c}{X} = \frac{1}{\lambda}\left(\sum_{h=1}^{H}\left(\frac{1}{q_z} + \psi^h\phi'(Z)\big(1 + m^h\big)\frac{\partial Z}{\partial q_z}\right)\frac{1}{Z} - \sum_{h=1}^{H}\frac{\theta^h}{q_x}\frac{1}{X}\right) \qquad (A4.18)$$

<u>Homogeneous, non-moral</u> $\left(\frac{\partial Z}{\partial q_z} = -\frac{Z}{q_z}, \frac{1}{X} = \frac{q_x}{q_z}\frac{1}{\sum_{h=1}^{H}\theta^h z^h}, m^h = 0\right)$:

$$\frac{\Delta Z^c}{Z} - \frac{\Delta X^c}{X} = -\frac{\psi H \phi'(Z)}{\lambda q_z} \tag{A4.19}$$

Heterogeneous, non-moral

$$\frac{\Delta Z^c}{Z} - \frac{\Delta X^c}{X} = -\frac{\left(\sum \psi^h\right)\phi'(Z)}{\lambda q_z} + \left(\frac{H}{Z} - \frac{\sum_{h=1}^{H} \theta^h}{\sum_{h=1}^{H} \theta^h z^h}\right) \tag{A4.20}$$

Homogeneous, moral $\left(\frac{\partial Z}{\partial q_z} = -\frac{Z}{q_z}\frac{1}{1+\frac{\sum m^h z^h}{Z}}, \frac{1}{X} = \frac{(1-\psi^h\phi'(Z)Z)q_x}{q_z}\frac{1}{\sum z^h\theta^h}\right)$:

$$\frac{\Delta Z^c}{Z} - \frac{\Delta X^c}{X} = \frac{1}{\lambda q_z Z}\left(\sum_{h=1}^{H}(1-\psi\phi'(Z)Z) - \sum_{h=1}^{H}(1-\psi\phi'(Z)Z)\right) = 0 \tag{A4.21}$$

Heterogeneous, moral

$$\frac{\Delta Z^c}{Z} - \frac{\Delta X^c}{X} = \frac{1}{\lambda q_z}\left(\sum_{h=1}^{H}\left(1 - \psi^h\phi'(Z)Z\frac{1+m^h}{1+\frac{\sum m^h z^h}{Z}}\right)\frac{1}{Z} - \sum_{h=1}^{H}\left(1-\psi^h\phi'(Z)Z\right)\frac{\theta^h}{\sum z^h\theta^h}\right)$$

$$\frac{\Delta Z^c}{Z} - \frac{\Delta X^c}{X} = \frac{1}{\lambda q_z Z}\left(\left(H - \frac{\sum_{H=1}^{H}\theta^h \sum_{h=1}^{H} z^h}{\sum_{h=1}^{H}\theta^h z^h}\right) - \phi'(Z)Z\left(\frac{Z\sum_{h=1}^{H}\left(\psi^h\left(1+m^h\right)\right)}{Z+\sum_{h=1}^{H} m^h z^h} - \frac{\sum_{h=1}^{H} z^h \sum_{h=1}^{H}\psi^h\theta^h}{\sum_{h=1}^{H} z^h\theta^h}\right)\right) \tag{4.22}$$

If the only difference is the damage function (i.e., income, clean good preference and leisure preference homogenous):

$$\frac{\Delta Z^c}{Z} - \frac{\Delta X^c}{X} = \frac{1}{\lambda q_z Z}\left(-\phi'(Z)Z\left(\frac{Z\sum_{h=1}^{H}\left(\psi^h\left(1+m^h\right)\right)}{Z+\sum_{h=1}^{H} m^h z^h} - \sum_{h=1}^{H}\psi^h\right)\right) \tag{4.23}$$

Since $m^h = \frac{(\theta^h+\eta^h)\psi^h\left(\phi''(Z)Z+\phi'(Z)\right)Z}{(1+\theta^h+\eta^h-\psi^h\phi'(Z)Z)(1-\psi^h\phi'(Z)Z)}$ depends on ψ^h it also varies across households.

$$\frac{\partial m^h}{\partial \psi^h}\frac{1}{m^h} = \frac{1}{\psi^h} + \frac{\phi'(Z)Z}{(1+\theta^h+\eta^h-\psi^h\phi'(Z)Z)} + \frac{\phi'(Z)Z}{(1-\psi^h\phi'(Z)Z)} > 0$$

Positive correlation between morality term and damage parameter. Therefore, assuming homogenous preferences for clean good and leisure and homogeneous income, will be a negative correlation between the morality term and dirty good consumption.

Since $z^h = \frac{(1-\psi^h\phi'(Z)Z)(I^h+w^h)}{(1+\theta^h+\eta^h-\psi^h\phi'(Z)Z)q_z}$,

$$\frac{\partial z^h}{\partial \psi^h} = z^h \frac{-(\theta^h+\eta^h)\phi'(Z)Z}{(1-\psi^h\phi'(Z)Z)(1+\theta^h+\eta^h-\psi^h\phi'(Z)Z)} < 0$$

As the parameter on the damage function increases, the Kantian consumption of the dirty good decreases. Therefore, assuming clean good preference, leisure preference and income constant, there would be a negative correlation between ψ^h and z^h.

This implies that in the first term inside the brackets, the numerator will be greater than the denominator, thus this term will be greater than the second term inside the bracket. This means overall the term will be negative, but it will be smaller than the absolute size homogenous non-moral.

When there is a difference in the damage that consumers experience, each consumer will seek to internalise the damages that they personally experience. This means that consumers who experience a higher damage, i.e. higher ψ^h, will consume less of the dirty good, whilst consumers who experience lower damages will consume more. Assuming that all other preference and income are homogeneous across agents, heterogeneity in damage functions results in a residual externality. When all other preferences and income are constant, each agent is weighing the gain from their own dirty good consumption (which will be the same for all agents) against the cost of everyone increasing their dirty good consumption (which differs according to ψ^h). Given the concave shape of the utility function, the lower consumption of people experiencing higher damages will not compensate for the higher consumption of people experiencing lower damages.

If we allow for income to vary across households, the effect of heterogeneous damages depends on the correlation between the damage parameter and income. If there is positive correlation between the damage parameter and income, then the negative correlation between ψ^h and z^h would reduce, resulting in a lower corrective element of the tax. Thus, we support Sandmo's findings, where higher income people suffer from pollution, the corrective element of taxation will be lower. In our case, this is due to higher income moral households having greater market power to bring the economy closer to the social optimum.

Appendix B: Appendix for Chapter 2

Appendix B1: Pareto Efficient Asset Pricing Rule

The first order conditions from optimising equation 2.8 with respect to consumption in both periods and with respect to the constraint $K \geq 0$ are,

$$\frac{\partial \mathcal{L}}{\partial c_1^h} = \mu^h \, u'\left(c_1^h\right) - \lambda_1 = 0, \tag{B1.1}$$

$$\frac{\partial \mathcal{L}}{\partial c_2^h} = \mu^h \beta u'\left(c_2^h\right) - \lambda_2 = 0\,, \tag{B1.2}$$

$$\frac{\partial \mathcal{L}}{\partial K} = -\lambda_1 + \lambda_2 R \leq 0\,, \tag{B1.3}$$

$$\frac{\partial \mathcal{L}}{\partial Z} = -\sum_{h=1}^{H} \mu^h \beta \eta^h v'(X) \psi F_z - \lambda_1 + \lambda_2 F_Z = 0. \tag{B1.4}$$

If the constraint $K \geq 0$ binds, then (B1.3) is negative. Divide equation (B1.4) by λ_2 and substitute in $\mu^h = \frac{\lambda_2}{\beta u'(c_2^h)}$ from equation (B1.2),

$$F_z(Z,L) - \frac{\lambda_1}{\lambda_2} = \sum_{h=1}^{H} \eta^h \frac{v'(X)}{u'\left(c_2^h\right)} \, \psi \, F_z(Z,L) \ . \tag{B1.5}$$

If the constraint $K \geq 0$ is not binding, then $\lambda_1 = \lambda_2 R$ and we have the Pareto optimum asset-pricing rule,

$$F_z(Z,L) - R = \sum_{h=1}^{H} \eta^h \frac{v'(X)}{u'\left(c_2^h\right)} \, \psi \, F_z(Z,L) \ . \tag{B1.6}$$

If the constraint $K \geq 0$ binds, use (B1.1) and (B1.2) in (B1.5), and we have the Pareto optimum asset-pricing rule,

$$F_z(Z,L) - \frac{u'\left(c_1^h\right)}{\beta u'\left(c_2^h\right)} = \sum_{h=1}^{H} \eta^h \frac{v'(X)}{u'\left(c_2^h\right)} \, \psi \, F_z(Z,L) \ . \tag{B1.7}$$

for any h.

Appendix B2: Return on the Dirty Asset

Given that the dirty firms' production function has constant returns to scale, the production function can be written as,

$$F(Z, L) = F_Z Z + F_L L\,. \tag{B2.1}$$

In equilibrium, the marginal production of labour will be equal to the wage rate, $F_L = w$, such that,

$$F(Z, L) = F_Z Z + wL. \tag{B2.2}$$

Equation B2.2 can be substituted into the return on the dirty asset such that,

$$P = \frac{F(Z, L) - wL}{Z} = F_Z(Z, L) \tag{B2.3}$$

Appendix B3: Higher η^h implies higher z^h

$$(F_z - R)z^h = \eta^h \frac{v(X)}{u'\left(c_2^h\right)} F_z Z \tag{B3.1}$$

Assuming aggregate consumption constant, take the differential of equation B3.1, rearrange to give,

$$\frac{\mathrm{d}z^h}{z^h} = \frac{\mathrm{d}\eta^h}{\eta^h} - \frac{u''\left(c_2^h\right)}{u'\left(c_2^h\right)} \mathrm{d}c_2^h \tag{B3.2}$$

Take the two budget constraints from equations 2.2 and 2.3, substitute first period budget constraint (2.2) into second period budget constraint (2.3) to give,

$$c_2^h = (F_z - R)z^h + wl_2^h + Rl_1 - Rc_1^h \tag{B3.3}$$

Take the differential of equation B3.3,

$$\mathrm{d}c_2^h = (F_z - R)\mathrm{d}z^h - R\,\mathrm{d}c_1^h \tag{B3.4}$$

Use the first order condition in equation 2.18,

$$u'\left(c_1^h\right) = \beta R\, u'\left(c_2^h\right) \tag{B3.5}$$

Take the differential of equation B3.5,

$$u''\left(c_2^h\right)\mathrm{d}c_1^h = \beta R u''\left(c_2^h\right)\mathrm{d}c_2^h \tag{B3.6}$$

Divide equation B3.6 by B3.5,

$$\frac{u''\left(c_1^h\right)}{u'\left(c_1^h\right)} \mathrm{d}c_1^h = \frac{u''\left(c_2^h\right)}{u'\left(c_2^h\right)}\ \mathrm{d}c_2^h$$

$$A_1^h \, \mathrm{d}c_1^h = A_2^h \, \mathrm{d}c_2^h \tag{B3.7}$$

Where $A_t^h = -\frac{u''(c_t^h)}{u'(c_t^h)}$.

Substitute equation B3.7 into equation B3.4,

$$\mathrm{d}c_2^h = (F_z - R)\mathrm{d}z^h - R\frac{A_2^h}{A_1^h}\mathrm{d}c_2^h$$

$$\mathrm{d}c_2^h = \left(\frac{A_1^h}{A_1^h + RA_2^h}\right)(F_z - R)\mathrm{d}z^h \tag{B3.8}$$

Substitute equation B3.8 into equation B3.2,

$$\frac{\mathrm{d}z^h}{z^h} = \frac{\mathrm{d}\eta^h}{\eta^h} + \left(\frac{A_1^h}{A_1^h + RA_2^h}\right)A_2^h(F_z - R)\mathrm{d}z^h$$

$$\frac{\mathrm{d}z^h}{z^h}\left(1 - \frac{A_1^h}{A_1^h + RA_2^h}A_2^h(F_z - R)z^h\right) = \frac{\mathrm{d}\eta^h}{\eta^h} \tag{B3.9}$$

Firstly, $\frac{A_1^h}{A_1^h+RA_2^h} < 1$ since $R > 0$ and $A_t^h > 0$ (due to utility being increasing and concave in consumption). Secondly, a sufficient condition for $A_2^h(F_z - R)z^h \leq 1$ is that $-\frac{u''(c_2^h)}{u'(c_2^h)}c_2^h \leq 1$. This can be seen by multiplying and dividing $A_2^h(F_z - R)z^h$ by c_2^h such that,

$$A_2^h(F_z - R)z^h = A_2^h c_2^h \frac{F_z - R}{(F_z - R)z^h + w^h l_2 + Rk}$$

Here, we can see that $\frac{F_z-R}{(F_z-R)z^h+w^h l_2+Rk} < 1$. If $A_2^h c_2^h \leq 1$, i.e., $-\frac{u''(c_2^h)}{u'(c_2^h)}c_2^h \leq 1$, this is sufficient for $A_2^h(F_z - R)z^h < 1$ which, together with $\frac{A_1^h}{A_1^h+RA_2^h} < 1$, is sufficient for the term within the bracket of equation B3.9 to be positive.

Therefore, given the sufficient condition that the Arrow-Pratt measure of relative risk-aversion is no greater than 1, a higher η^h will correspond to a higher z^h.

Appendix B4: Deriving how Aggregate Dirty Investment changes with the Proportion of Non-Kantians

B4.1 Inclusive Kantians

Starting from the pollution premium in the inclusive partially Kantian economy (equation 2.18), suppose that all Kantian agents are identical,

$$\frac{F_z - R}{F_z} = \frac{Z}{Z - Z^n}(1-\delta)N\eta\frac{v'(X)}{u'\left(c_2^h\right)}\psi, \tag{B4.1}$$

Where $\delta = \frac{Nn}{N}$ represents the proportion of non-Kantians in the economy. We can then begin to investigate how equilibrium aggregate dirty investment changes when the proportion of non-Kantians changes by taking the full differential of equation B4.1, where $\eta, \psi, v'(X)$ and N are fixed.

$$\begin{aligned}\frac{RF_{zz}}{F_z F_z}\,dZ = &-\left[\frac{Z}{Z^k}N\eta\frac{v'(X)}{u(c_2^{kp})}\psi\right]d\delta + \left[-\frac{Z}{Z^k}(1-\delta)N\,\eta\frac{v'(X)}{u'\left(c_2^h\right)}\psi\frac{u''\left(c_2^{kp}\right)}{u'\left(c_2^{kp}\right)}\right]dc_2^h \\ &-\left[\frac{Z^n}{{Z^k}^2}(1-\delta)N\eta\frac{v'(X)}{u'\left(c_2^{kp}\right)}\psi\right]dZ + \left[\frac{Z}{{Z^k}^2}(1-\delta)N\eta\frac{v'(X)}{u'(c_2^{kp})}\psi\right]dZ^n\end{aligned} \tag{B4.2}$$

To obtain $\frac{\partial Z}{\partial \delta}$, we first need to investigate how Z^n and c_2^h change with regards to changes in aggregate dirty investment and the proportion of non-Kantians.

To investigate dZ^n we can start with the expression for non-Kantian investment. We know that non-Kantians invest solely in the dirty firm and that their investment level depends upon the return from this investment and on how much they value consumption in period two versus period one. The inverse of their first order condition, $u'\left(c_1^h\right) = \beta F_z u'\left(c_2^h\right)$, is $c_1^h = c_2^h\, u'^{-1}(\beta F_z)$. Substituting the non-Kantian's budget constraint, which excludes clean investments gives an expression for non-Kantian dirty investment.

$$z^n = \frac{l_1 - wl_2 {u'}^{-1}(\beta F_z)}{1 + F_z\, u'^{-1}(\beta F_z)} \tag{B4.3}$$

Assuming that non-Kantian agents are identical, aggregate non-Kantian investment would be,

$$Z^n = N^n\left(\frac{l_1 - wl_2 {u'}^{-1}(\beta F_z)}{1 + F_z\, u'^{-1}(\beta F_z)}\right) \tag{B4.4}$$

Multiply and divide by N, then substitute $wL = wNl_2 = F - F_z Z$ from production equilibrium in equation B2.2 to give,

$$Z^n = \frac{N^n}{N}\left(\frac{Nl_1 - {u'}^{-1}(\beta F_z)(F - F_z Z)}{1 + F_z\, u'^{-1}(\beta F_z)}\right) \tag{B4.5}$$

Take the total differential of equation B4.5, using the fact that that partial differential of the inverse of marginal utility $u'^{-1}(\beta F_z)$ with respect of F_z is equal to $\frac{\partial u'^{-1}(\beta F_Z)}{\partial F_Z} = \frac{\beta}{u''(c_2^n)}$, and with respect to Z is equal to $\frac{\partial u'^{-1}(\beta F_Z)}{\partial Z} = \frac{\beta F_{ZZ}}{u''(c_2^n)}$.

$$dZ^n = \frac{Z^n}{\delta}\, d\delta +$$
$$\left(\frac{u'^{-1}(\beta F_z)F_{zz}Z - (F - F_z Z)\frac{\beta F_{zz}}{u''(c_2^n)}}{1 + u'^{-1}(\beta F_z)F_z} - \frac{\left(Nl_1 - u'^{-1}(\beta F_z)(F - F_z Z)\right)\left(F_{zz}u'^{-1}(\beta F_z) + \frac{F_z \beta F_{zz}}{u''(c_2^n)}\right)}{(1 + u'^{-1}(\beta F_z)F_z)^2} \right) dZ \quad (B4.6)$$

Dividing equation B4.6 by Z^n and simplifying gives,

$$dZ^n = Z^n \left[\frac{1}{\delta}\, d\delta + F_{zz} \left(\frac{u'^{-1}(\beta F_z)[Z - Nl_1 + Fu'^{-1}(\beta F_z)] + \frac{\beta}{u''(c_2^n)}[-Nl_1 F_z - wNl_2]}{\delta\left(Nl_1 - u'^{-1}(\beta F_z)(F - F_z Z)\right)(1 + u'^{-1}(\beta F_z)F_z)} \right) dZ \right] \quad (B4.7)$$

The first term in the numerator cancels out in equilibrium since, $u'(l_1 - z) = \beta F_z u'(wl_2 + F_z Z)$ implies that $Nl_1 - Z = u'^{-1}(\beta F_z)(Nwl_2 + F_z Z) = u'^{-1}(\beta F_z)F$, such that $Z - Nl_1 + Fu'^{-1}(\beta F_z) = 0$.

$$dZ^n = Z^n \left[\frac{1}{\delta}\, d\delta + F_{zz} \left(\frac{\frac{\beta}{u''(c_2^n)}[-Nl_1 F_z - wNl_2]}{\delta\left(Nl_1 - u'^{-1}(\beta F_z)(F - F_z Z)\right)(1 + u'^{-1}(\beta F_z)F_z)} \right) dZ \right]. \quad (B4.8)$$

Let

$$dZ^n = Z^n \left[\frac{1}{\delta}\, d\delta + F_{zz} A dZ \right], \quad (B4.9)$$

where $A = \frac{\frac{\beta}{u''(c_2)}[-Nl_1 F_z - wNl_2]}{\delta(Nl_1 - u'^{-1}(\beta F_z)wNl_2)(1 + u'^{-1}(\beta F_z)F_z)} > 0$[1]. This implies that as the proportion of non-Kantians in the economy rises, the aggregate investment of non-Kantians rises due to a higher number of non-Kantians investing, however, this aggregate investment falls with overall investment in the dirty firm,

[1] The numerator will be positive due to $u''(c_2) < 0, Nl_1 F_z > 0, wNl_2 > 0$. The first term in the denominator will be positive, since, given that investors find it optimal to invest in period 1, then $u(l_1) < \beta F_z\, u(wl_2)$, therefore $Nl_1 > u'^{-1}(\beta F_z)wNl_2 = u'^{-1}(\beta F_z)(F - F_z Z)$. The second term in the denominator is clearly positive due to $u'^{-1}(\beta F_z) > 0, F_z > 0$.

implying that each individual non-Kantian household is investing less due to the declining marginal productivity of capital lowering returns.

To investigate dc_2^{kp} we need to look at how Kantian consumption changes with respect to changes in the proportion of non-Kantians and the subsequent changes in dirty investment, we can take the total differential of Kantian consumption.

Starting from the Kantian first order condition for clean investment $u'(c_1) = \beta R u'(c_2)$, we can take the inverse, $c_1 = c_2\, u'^{-1}(\beta R)$. Substituting in the Kantian budget constraints (equations 2.2 and 2.3) we have,

$$l_1 - wl_2 u'^{-1}(\beta R) = z^h \left(1 + F_z u'^{-1}(\beta R)\right) + k\left(1 + Ru'^{-1}(\beta R)\right), \qquad (B4.10)$$

From which we can derive an expression for Kantian clean investment in terms of dirty investment, investment returns, labour and utility.

$$k = \frac{l_1 - z^h - wl_2 u'^{-1}(\beta R) - z^h F_z u'^{-1}(\beta R)}{1 + Ru'^{-1}(\beta R)} \qquad (B4.11)$$

To obtain an expression for period 2 consumption in terms of dirty investment, investment returns, and fixed parameters, equation B4.11 can be substituted into the Kantian second period budget constraint.

$$c_2 = wl_2 + F_z z^h + R\left(\frac{l_1 - z^h - wl_2 u'^{-1}(\beta R) - z^h F_z u'^{-1}(\beta R)}{1 + Ru'^{-1}(\beta R)}\right) \qquad (B4.12)$$

Equation B4.12 can be simplified to,

$$c_2 = \frac{\tilde{\beta}}{N}\left(wNl_2 + RNl_1 + \frac{(F_Z - R)(Z - Z^n)}{1 - \delta}\right)$$

Where $\tilde{\beta} = \frac{1}{1 + Ru'^{-1}(\beta R)}$ is a constant.

Substitute in $wL = wNl_2 = F - F_z Z$ then add and subtract $(F_z - R)Z$,

$$c_2 = \frac{\tilde{\beta}}{N}\left(F - F_z Z + (F_z - R)Z + RNl_1 - (F_z - R)Z + \frac{(F_Z - R)(Z - Z^n)}{1 - \delta}\right)$$

$$c_2^{kp} = \frac{\tilde{\beta}}{N}\left[F - RZ + RNl_1 - (F_z - R)Z + \frac{(F_z - R)(Z - Z^n)}{(1-\delta)}\right] \quad (B4.13)$$

Take the total differential,

$$dc_2^{kp} = \frac{\tilde{\beta}}{N}\left[\left\{-F_{zz}Z + \left(\frac{F_z - R + F_{zz}(Z - Z^n)}{(1-\delta)}\right)\right\}dZ - \left\{\frac{(F_z - R)}{(1-\delta)}\right\}dZ^n + \left\{\frac{(F_z - R)(Z - Z^n)}{(1-\delta)^2}\right\}d\delta\right] (B4.14)$$

Substitute in equation B4.9 for dZ^n,

$$dc_2^{kp} = \frac{\tilde{\beta}}{N}\left[\begin{array}{c}\left\{-F_{zz}Z + \left(\frac{F_z - R + F_{zz}(Z - Z^n)}{(1-\delta)}\right)\right\}dZ - \left\{\frac{(F_z - R)}{(1-\delta)}\right\}Z^n\left[\frac{1}{\delta}\,d\delta + F_{zz}AdZ\right] \\ + \left\{\frac{(F_z - R)(Z - Z^n)}{(1-\delta)^2}\right\}d\delta\end{array}\right] \quad (B4.15)$$

$$dc_2^{kp} = \frac{\tilde{\beta}}{N}\left[\begin{array}{c}\left(F_{zz}\left(-Z + \frac{(Z - Z^n)}{1-\delta}\right) + \frac{F_z - R}{(1-\delta)}(1 - Z^n\,F_{zz}A)\right)dZ \\ + \frac{(F_z - R)}{(1-\delta)}\left(\frac{(Z - Z^n)}{(1-\delta)} - \frac{Z^n}{\delta}\right)d\delta\end{array}\right]$$

Rearranging this gives,

$$dc_2^{kp} = \frac{\tilde{\beta}}{N}\left[\left(F_{zz}\left(-Z + \frac{Z^kN}{N^k}\right) + \frac{F_z - R}{(1-\delta)}(1 - Z^n\,F_{zz}A)\right)dZ + \frac{(F_z - R)}{(1-\delta)}\left(\frac{Z^kN}{N^k} - \frac{Z^nN}{N^n}\right)d\delta\right] (B4.16)$$

$$dc_2^{kp} = \frac{\tilde{\beta}}{N}[BdZ + Dd\delta] \quad (B4.17)$$

Where $B = \left(F_{zz}\left(-Z + \frac{Z^kN}{N^k}\right) + \frac{F_z - R}{(1-\delta)}(1 - Z^n\,F_{zz}A)\right) > 0$[2], and $D = \frac{(F_z - R)}{(1-\delta)}\left(\frac{Z^kN}{N^k} - \frac{Z^nN}{N^n}\right) < 0$[3].

Substituting equation B4.9 for dZ^n and equation B4.17 for dc_2^h into the total differential of the partially Kantian pollution premium (equation B4.2) gives:

---

[2] Since $F_{zz} < 0$ and $\frac{Z^k}{N^k} < \frac{Z}{N}$ in the presence of non-Kantians, the first term will be positive. Further, $(F_z - R) > 0$, $0 < \delta < 1$, and $A > 0$ imply that the second term is also positive.

[3] In the presence of Kantians, $(F_z - R) > 0$ and $0 < \delta < 1$ make the first term positive, and $\frac{Z^k}{N^k} < \frac{Z^n}{N^n}$ implies that the term this is multiplied with is negative.

$$\left[\frac{RF_{zz}}{F_zF_z}+\frac{Z}{Z^k}(1-\delta)N\,\eta\frac{v'(X)}{u'\left(c_2^h\right)}\psi\left[\frac{u''\left(c_2^{kp}\right)}{u'\left(c_2^{kp}\right)}\frac{\tilde{\beta}}{N}\,B+\frac{Z^n}{ZZ^k}-\frac{Z^n}{Z^k}F_{zz}A\right]\right]dZ$$
$$=\left[\frac{Z}{Z^k}N\eta\frac{v'(X)}{u(c_2^{kp})}\psi\left[-1-(1-\delta)\frac{u''\left(c_2^{kp}\right)}{u'\left(c_2^{kp}\right)}\frac{\tilde{\beta}}{N}D+\frac{Z^n}{Z^k}\frac{(1-\delta)}{\delta}N\right]\right]d\delta \tag{B4.18}$$

$$\frac{dZ}{d\delta}=\frac{\left[\frac{Z}{Z^k}N\eta\frac{v'(X)}{u(c_2^{kp})}\psi\left[-1-(1-\delta)\frac{u''\left(c_2^{kp}\right)}{u'\left(c_2^{kp}\right)}\frac{\tilde{\beta}}{N}D+\frac{Z^n}{Z^k}\frac{(1-\delta)}{\delta}N\right]\right]}{\left[\frac{RF_{zz}}{F_zF_z}+\frac{Z}{Z^k}(1-\delta)N\,\eta\frac{v'(X)}{u'\left(c_2^h\right)}\psi\left[\frac{u''\left(c_2^{kp}\right)}{u'\left(c_2^{kp}\right)}\frac{\tilde{\beta}}{N}\,B+\frac{Z^n}{ZZ^k}-\frac{Z^n}{Z^k}F_{zz}A\right]\right]} \tag{B4.19}$$

Overall, the sign of equation B4.19 will depend upon the functional forms of the utility and production functions and the values of the parameters within the equations. There are multiple effects occurring simultaneously when the proportion of non-Kantians increases in the economy, which of these effects dominates cannot be solved analytically.

B4.2 Exclusive Kantians

Start from the pollution premium in the exclusive Kantian economy in equation 2.23. Assuming that Kantian agents are identical we can simplify this to,

$$\frac{(F_Z-R)}{F_z}=\frac{(N-N^n)\eta\psi v}{u\left(c_2^h\right)}. \tag{B4.20}$$

Take the total differential of equation B4.20.

$$\frac{F_{zz}R}{F_zF_z}\,dZ=-\frac{N\eta\psi v}{u'\left(c_2^h\right)}\,d\delta-\frac{(N-N^n)\eta\psi v}{u'\left(c_2^h\right)}\frac{u''\left(c_2^h\right)}{u'\left(c_2^h\right)}\,dc_2^h \tag{B4.21}$$

Substitute equation B.C17 in for dc_2^h.

$$\frac{F_{zz}R}{F_zF_z}\,dZ=-\frac{N\eta\psi v}{u'\left(c_2^h\right)}\,d\delta-\frac{(N-N^n)\eta\psi v}{u'\left(c_2^h\right)}\frac{u''\left(c_2^h\right)}{u'\left(c_2^h\right)}\left[\frac{\tilde{\beta}}{N}[BdZ+Dd\delta]\right] \tag{B4.22}$$

Re-arrange,

$$\left[\frac{F_{zz}R}{F_Z F_z}+\frac{(N-N^n)\eta\psi v}{u'\left(c_2^h\right)}\frac{u''\left(c_2^h\right)}{u'\left(c_2^h\right)}\frac{\tilde{\beta}}{N}B\right]dZ=\left[-\frac{N\eta\psi v}{u'\left(c_2^h\right)}-\frac{(N-N^n)\eta\psi v}{u'\left(c_2^h\right)}\frac{u''\left(c_2^h\right)}{u'\left(c_2^h\right)}\frac{\tilde{\beta}}{N}D\right]d\delta$$

$$\frac{dZ}{d\delta}=\frac{\left[-\frac{N\eta\psi v}{u'\left(c_2^h\right)}-\frac{(N-N^n)\eta\psi v}{u'\left(c_2^h\right)}\frac{u''\left(c_2^h\right)}{u'\left(c_2^h\right)}\frac{\tilde{\beta}}{N}D\right]}{\left[\frac{F_{zz}R}{F_Z F_z}+\frac{(N-N^n)\eta\psi v}{u'\left(c_2^h\right)}\frac{u''\left(c_2^h\right)}{u'\left(c_2^h\right)}\frac{\tilde{\beta}}{N}B\right]}>0 \qquad (B4.23)$$

$$\frac{dZ}{d\delta}=\frac{\left[\frac{Z}{Z^k}\frac{N\eta\psi v}{u'\left(c_2^h\right)}\left[-1-(1-\delta)\frac{u''\left(c_2^{kp}\right)}{u'\left(c_2^{kp}\right)}\frac{\tilde{\beta}}{N}D+\frac{Z^n}{Z^k}\frac{(1-\delta)}{\delta}N\right]\right]}{\left[\frac{RF_{zz}}{F_z F_z}+\frac{Z}{Z^k}(1-\delta)N\,\eta\frac{v'(X)}{u'\left(c_2^h\right)}\psi\left[\frac{u''\left(c_2^{kp}\right)}{u'\left(c_2^{kp}\right)}\frac{\tilde{\beta}}{N}B+\frac{Z^n}{ZZ^k}-\frac{Z^n}{Z^k}F_{zz}A\right]\right]}$$

We can see that the numerator is negative, since the first term is composed of positive element and is subtracted, whilst the second term has two negative elements, $u''\left(c_2^h\right)<0$ and $D<0$, which multiply to become positive, and this term is also subtracted. The numerator is also negative, since the first term has one negative element, $F_{zz}<0$, and the second term has one negative element, $u''\left(c_2^h\right)<0$. Overall, this makes the differential in equation 2.23 positive, demonstrating that in an economy with exclusive Kantians, the amount of dirty investment will rise with the proportion of non-Kantians.

Appendix B5: Simulation equations

To simulate the inclusive Kantian equilibrium, we use the analytical equilibrium from the model above and solve it for specific values of the constant parameters. We vary the proportion of non-Kantian agents in the economy to investigate how Kantian and non-Kantian portfolios change with regards to the proportion of non-Kantians.

From the Kantian's first order condition for clean investment, equation 2.16, we know that

$$u'(c_1)=\beta R\,u'(c_2)$$

Assuming logarithmic utility functions we can substitute in $u'(c)=\frac{1}{c}$ and the two budget constraints in equations 2.2 and 2.3 to give,

$$wl_2 + Rk + F_Z z^k = \beta R\left(l_1 - k - z^k\right)$$

This can be rearranged to give an equation for Kantian clean investment in terms of returns on investment, dirty investment, and labour,

$$k = \frac{1}{R}\left(\frac{\beta}{1+\beta} Rl_1 - \frac{\left(wl_2 + z^k(\beta R + F_z)\right)}{1+\beta}\right) \qquad (B5.1)$$

We can then take the equilibrium condition for Kantians from equation 2.17, where we assume that $v(X)$ is linear such that $v'(X) = v$, and $\frac{1}{u'(c_2)} = c_2$,

$$(F_z - R)z^k = \psi v \eta c_2 F_z Z.$$

substitute in $c_2 = \frac{\beta}{1+\beta}\left((F_Z - R)z^k + wl_2 + Rl_1\right)$ from the budget constraint in equation 2.3,

$$(F_z - R)z^k = \psi v \eta F_z Z \frac{\beta}{1+\beta}\left((F_Z - R)z^k + wl_2 + Rl_1\right).$$

Simplify this to,

$$(F_z - R)z^k = \theta \frac{F_z Z}{N}\left((F_Z - R)z^k + wl_2 + Rl_1\right) \qquad (B5.2)$$

Where $\theta = \psi v \eta N \frac{\beta}{1+\beta}$. Equation B5.2 can be rearranged to give an expression for Kantian dirty investment in terms of returns on investment, aggregate dirty investment and labour.

$$z^k = \frac{\theta \frac{F_Z Z}{N}}{1 - \theta \frac{F_Z Z}{N}} \frac{\frac{F - F_Z Z}{N} + Rl_1}{F_z - R} \qquad (B5.3)$$

Where $wl_2 = F_Z \frac{Z}{N}$, which arises from the production function equilibrium in equation B.B2, whereby $wl_2 = F - F_z Z$, which in the case of a Cobb-Douglas production with $\alpha = \frac{1}{2}$, $F(Z, L) = Z^{\frac{1}{2}} L^{\frac{1}{2}}$, would give $wl_2 = F_Z \frac{Z}{N}$.

Finally, an expression for non-Kantian dirty investment can be derived from the non-Kantian's first order condition for dirty investment in the scenario where they only invest in the dirty firm.

$$u'(c_1) = \beta F_z\, u'(c_2)$$

Substituting in for logarithmic utility and for the Kantian's budget constraints of $c_1 = l_1 - z_n$ and $c_2 = wl_2 + F_z z_n$,

$$wl_2 + F_z z^n = \beta F_z (l_1 - z^n)$$

$$z^n = \frac{\beta}{1+\beta}\, l_1 - \frac{1}{1+\beta}\frac{wl_2}{F_z}$$

Substituting in $wl_2 = \frac{F - F_z Z}{N}$,

$$z^n = \frac{\beta}{1+\beta}\, l_1 - \frac{1}{1+\beta}\frac{F - F_z Z}{F_z N} \qquad (B5.4)$$

Overall, equations B5.1, B5.3 and B5.4 give the expressions for the portfolios of the Kantian and the non-Kantian agents.

Average dirty investment can be calculated by substituting B5.3 and B5.4 into the equation for average dirty investment in the partially Kantian economy, $\frac{Z}{N} = \frac{N^k}{N}\, z^k + \frac{N^n}{N}\, z^n$

$$\frac{Z}{N} = \frac{N^k}{N}\left(\frac{\theta \frac{F_Z Z}{N}}{1 - \theta \frac{F_Z Z}{N}}\frac{\frac{F_Z Z}{N} + R l_1}{F_z - R}\right) + \frac{N^n}{N}\left(\frac{\beta}{1+\beta}\, l_1 - \frac{1}{1+\beta}\frac{Z}{N}\right)$$

$$\frac{Z}{N}\left(1 + \frac{N^n}{N}\frac{1}{1+\beta}\right) = \left(1 - \frac{N^n}{N}\right)\left(\frac{\theta \frac{F_Z Z}{N}}{1 - \theta \frac{F_Z Z}{N}}\frac{\frac{F_Z Z}{N} + R l_1}{F_z - R}\right) + \frac{N^n}{N}\frac{\beta}{1+\beta}\, l_1$$

$$\frac{Z}{N}\left(1 + \frac{N^n}{N}\frac{1}{1+\beta}\right) = \left(1 - \frac{N^n}{N}\right)\left(\frac{\frac{1}{2}\theta \left(\frac{Z}{N}\right)^{\frac{1}{2}}}{1 - \frac{1}{2}\theta \left(\frac{Z}{N}\right)^{\frac{1}{2}}}\frac{\frac{1}{2}\left(\frac{Z}{N}\right)^{\frac{1}{2}} + R l_1}{\left(\frac{Z}{N}\right)^{-\frac{1}{2}} - R}\right) + \frac{N^n}{N}\frac{\beta}{1+\beta}\, l_1 \qquad (B5.5)$$

To investigate the case of exclusive Kantianism, we would use the same equations for the Kantian clean investment and the non-Kantian dirty investment, however, we would derive a different equation for the Kantian dirty investment based on exclusive Kantian optimisation. Instead for drawing on equation 2.17, where the Kantians assume that all agents, Kantian and non-Kantian, will deviate the same proportion within their moral optimisation, we draw on equation 2.22 where they assume that only fellow Kantian agents will deviate.

$$z^k(F_z - R) = \eta^h \psi v F_Z(Z,L) Z^K \frac{\beta}{1+\beta}\Big((F_Z - R)z^k + wl_2 + Rl_1\Big)$$

$$z^k(F_z - R) = \frac{\theta F_z N^k z^k}{N}\Big((F_Z - R)z^k + wl_2 + Rl_1\Big)$$

$$z^k = \frac{\frac{\theta F_z N^k z^k}{N}}{1 - \frac{\theta F_z N^k z^k}{N}} \frac{\left(\frac{F - F_z Z}{N} + Rl_1\right)}{(F_z - R)} \qquad (B5.6)$$

To investigate how aggregate dirty investment changes as the proportion of non-Kantians in the economy changes, we run simulations of equations B5.1, B5.3, B5.4, and B5.5. We assume that the production function is Cobb-Douglas with a capital input share of $\alpha = \frac{1}{2}$, such that $F(Z,L) = Z^{\frac{1}{2}}L^{\frac{1}{2}}$, where $L = Nl_2 = N$ since it is assumed that $l_2 = 1$. The equations become,

$$k = \frac{1}{R}\left(\frac{\beta}{1+\beta} Rl_1 - \frac{\left(\frac{1}{2}Z^{\frac{1}{2}}N^{-\frac{1}{2}} + z^k\left(\beta R + \frac{1}{2}Z^{-\frac{1}{2}}N^{\frac{1}{2}}\right)\right)}{1+\beta}\right) \qquad (B5.7)$$

$$z^{k\,(Inclusive)} = \frac{\frac{1}{2}\theta Z^{\frac{1}{2}}N^{-\frac{1}{2}}}{1 - \frac{1}{2}\theta Z^{\frac{1}{2}}N^{-\frac{1}{2}}} \frac{\frac{1}{2}Z^{\frac{1}{2}}N^{-\frac{1}{2}} + Rl_1}{\frac{1}{2}Z^{-\frac{1}{2}}N^{\frac{1}{2}} - R} \qquad (B5.8)$$

$$z^n = \frac{\beta}{1+\beta} l_1 - \frac{1}{1+\beta}\frac{Z}{N} \qquad (B5.9)$$

$$z^{k\,(Exclusive)} = \frac{\frac{1}{2}\theta Z^{-\frac{1}{2}}N^{-\frac{1}{2}}(N - N^n)z^k}{1 - \frac{1}{2}\theta Z^{-\frac{1}{2}}N^{-\frac{1}{2}}(N - N^n)z^k} \frac{\frac{1}{2}Z^{\frac{1}{2}}N^{-\frac{1}{2}} + Rl_1}{\frac{1}{2}Z^{-\frac{1}{2}}N^{\frac{1}{2}} - R} \qquad (B5.10)$$

To conduct these simulations, we must assign the constants values with are representative of a real market scenario. We use $\beta = 0.96, R = 1.25, l_1 = 0.225$ and $\theta = 0.181$. We also assume that $N = 1$ and solve the set of equations for values of $N^n \in [0,1]$.

We investigate the sensitivity of these results to variations in the functional forms of the production function and the utility function.

Firstly, we repeat the simulations with a Cobb-Douglas function with a capital share of $\alpha = \frac{1}{3}$, such that $F(Z, L) = Z^{\frac{1}{3}}L^{\frac{2}{3}}$. We find that in this case, the same patterns of results hold as the proportion of non-Kantians in the economy investments. The main difference is that for every proportion of non-Kantians, the overall level of dirty investment in the economy is lower, but that the overall level of production by the dirty firm is higher.

$$F(Z, L) = Z^{\frac{1}{3}}N^{\frac{2}{3}},\ \ F_z(Z, L) = \frac{1}{3}Z^{-\frac{2}{3}}N^{\frac{2}{3}}, wl_2 = \frac{F - F_z Z}{N} = \frac{2}{3}Z^{\frac{1}{3}}N^{-\frac{1}{3}}$$

$$k = \frac{1}{R}\left(\frac{\beta}{1+\beta}\,Rl_1 - \frac{\left(\frac{2}{3}Z^{\frac{1}{3}}N^{-\frac{1}{3}} + z^k\left(\beta R + \frac{1}{3}Z^{-\frac{2}{3}}N^{\frac{2}{3}}\right)\right)}{1+\beta}\right) \qquad (B5.11)$$

$$z^{k\ (Inclusive)} = \frac{\frac{1}{3}\theta Z^{\frac{1}{3}}N^{-\frac{1}{3}}}{1 - \frac{1}{3}\theta Z^{\frac{1}{3}}N^{-\frac{1}{3}}}\,\frac{\frac{2}{3}Z^{\frac{1}{3}}N^{-\frac{1}{3}} + Rl_1}{\frac{1}{3}Z^{-\frac{2}{3}}N^{\frac{2}{3}} - R} \qquad (B5.12)$$

$$z^n = \frac{\beta}{1+\beta}\,l_1 - \frac{1}{1+\beta}\frac{2Z}{N} \qquad (B5.13)$$

$$z^{k\ (Exclusive)} = \frac{\frac{1}{3}\theta Z^{-\frac{2}{3}}N^{-\frac{1}{3}}(N - N^n)z^k}{1 - \frac{1}{3}\theta Z^{-\frac{2}{3}}N^{-\frac{1}{3}}(N - N^n)z^k}\,\frac{\frac{2}{3}Z^{\frac{1}{3}}N^{-\frac{1}{3}} + Rl_1}{\frac{1}{3}Z^{-\frac{2}{3}}N^{\frac{2}{3}} - R} \qquad (B5.14)$$

Secondly, we repeat the simulations with a Stone-Geary utility function, whereby the investor has a baseline level of consumption that they must achieve in a give period. We investigate the difference between placing this restriction on first period consumption and second period consumption. We set this restriction at 10% of the optimal period 2 consumption in the fully non-Kantian economy.

$$U^h = u(c_1^h) + \beta\left[u(c_2^h - s) + \eta^h v(X)\right]$$

$$u'(c_1) = \beta R\, u'(c_2 - s)$$

$$wl_2 + Rk + F_Z z^k - s = \beta R(l_1 - k - z^k)$$

$$k = \frac{1}{R}\left(\frac{\beta}{(1+\beta)} R l_1 - \frac{(wl_2 + (\beta R + F_z) z^k)}{(1+\beta)} + \frac{1}{(1+\beta)} s\right) \qquad (B5.15)$$

$$(F_z - R) z^k = \psi v \eta c_2 F_z Z.$$

$$(F_z - R) z^k = \psi v \eta F_z Z \left(\frac{\beta}{1+\beta}\left((F_Z - R) z^k + wl_2 + Rl_1\right) - s\right).$$

$$(F_z - R) z^k = \theta \frac{F_z Z}{N}\left((F_Z - R) z^k + wl_2 + Rl_1 - \frac{1+\beta}{\beta}\, s\right)$$

$$z^{k,Inclusive} = \frac{\theta \frac{F_Z Z}{N}}{1 - \theta \frac{F_Z Z}{N}} \frac{\frac{F - F_Z Z}{N} + Rl_1 - \frac{1+\beta}{\beta}\, s}{F_z - R} \qquad (B5.16)$$

$$u'(c_1) = \beta F_z\, u'(c_2 - s)$$

$$wl_2 + F_z z^n - s = \beta F_z (l_1 - z^n)$$

$$z^n = \frac{\beta}{1+\beta} l_1 - \frac{F - F_z Z}{F_z N(1+\beta)} + \frac{s}{F_z(1+\beta)} \qquad (B5.17)$$

$$z^{k,Exclusive} = \frac{\frac{\theta F_Z (N - N^n) z^k}{N}}{\left(1 - \frac{\theta F_Z (N - N^n) z^k}{N}\right)} \frac{\left(wl_2 + Rl_1 - \frac{1+\beta}{\beta}\, s\right)}{(F_z - R)} \qquad (B5.18)$$

Substituting in $F(Z,L) = Z^{\frac{1}{2}} L^{\frac{1}{2}}$, $F_z = \frac{1}{2} Z^{-\frac{1}{2}} L^{\frac{1}{2}}$, $wl_2 = \frac{1}{2} Z^{\frac{1}{2}} N^{-\frac{1}{2}}$

$$k=\frac{1}{R}\left(\frac{\beta}{(1+\beta)}Rl_1-\frac{\left(\frac{1}{2}Z^{\frac{1}{2}}N^{-\frac{1}{2}}+\left(\beta R+\frac{1}{2}Z^{-\frac{1}{2}}N^{\frac{1}{2}}\right)z^k\right)}{(1+\beta)}+\frac{1}{(1+\beta)}s\right) \qquad (B5.19)$$

$$z^{k\,(Inclusive)}=\frac{\frac{1}{2}\theta Z^{\frac{1}{2}}N^{-\frac{1}{2}}}{1-\frac{1}{2}\theta Z^{\frac{1}{2}}N^{-\frac{1}{2}}}\frac{\frac{1}{2}Z^{\frac{1}{2}}N^{-\frac{1}{2}}+Rl_1-\frac{1+\beta}{\beta}\,s}{\frac{1}{2}Z^{-\frac{1}{2}}L^{\frac{1}{2}}-R} \qquad (B5.20)$$

$$z^n=\frac{\beta}{1+\beta}l_1-\frac{Z}{N(1+\beta)}+\frac{s}{\frac{1}{2}Z^{-\frac{1}{2}}L^{\frac{1}{2}}(1+\beta)} \qquad (B5.21)$$

$$z^{k,Exclusive}=\frac{\frac{1}{2}\theta Z^{-\frac{1}{2}}N^{-\frac{1}{2}}(N-N^n)z^k}{\left(1-\frac{1}{2}\theta Z^{-\frac{1}{2}}N^{-\frac{1}{2}}(N-N^n)z^k\right)}\frac{\left(\frac{1}{2}Z^{\frac{1}{2}}N^{-\frac{1}{2}}+Rl_1-\frac{1+\beta}{\beta}\,s\right)}{\left(\frac{1}{2}Z^{-\frac{1}{2}}N^{\frac{1}{2}}-R\right)} \qquad (B5.22)$$

If we now have a minimum consumption in period 1:

$$U^h=u\left(c_1^h-s\right)+\beta\left[u\left(c_2^h\right)+\eta^h v(X)\right]$$

$$u'(c_1-s)=\beta R\,u'(c_2)$$

$$wl_2+Rk+F_Z z^k=\beta R\left(l_1-k-z^k-s\right)$$

$$k=\frac{1}{R}\left(\frac{\beta}{(1+\beta)}R(l_1-s)-\frac{\left(wl_2+(\beta R+F_z)z^k\right)}{(1+\beta)}\right) \qquad (B5.23)$$

$$(F_z-R)z^k=\psi v\eta c_2F_zZ.$$

$$(F_z-R)z^k=\psi v\eta F_zZ\left(\frac{\beta}{1+\beta}\left((F_Z-R)z^k+wl_2+Rl_1\right)\right).$$

$$(F_z-R)z^k=\theta\frac{F_zZ}{N}\left((F_Z-R)z^k+wl_2+Rl_1\right)$$

$$z^{k,Inclusive}=\frac{\theta\frac{F_ZZ}{N}}{1-\theta\frac{F_ZZ}{N}}\frac{\frac{F-F_ZZ}{N}+Rl_1}{F_z-R} \qquad (B5.24)$$

$$u'(c_1 - s) = \beta F_z\, u'(c_2)$$

$$wl_2 + F_z z^n = \beta F_z (l_1 - z^n - s)$$

$$z^n = \frac{\beta}{1+\beta}(l_1 - s) - \frac{F - F_z Z}{F_z N(1+\beta)} \qquad (B5.25)$$

$$z^{k,Exclusive} = \frac{\frac{\theta F_Z (N - N^n) z^k}{N}}{\left(1 - \frac{\theta F_Z (N - N^n) z^k}{N}\right)} \frac{(wl_2 + Rl_1)}{(F_z - R)} \qquad (B5.26)$$

Substituting in $F(Z, L) = Z^{\frac{1}{2}} L^{\frac{1}{2}}$, $F_z = \frac{1}{2} Z^{-\frac{1}{2}} L^{\frac{1}{2}}$

$$k = \frac{1}{R}\left(\frac{\beta}{(1+\beta)} R(l_1 - s) - \frac{\left(\frac{1}{2} Z^{\frac{1}{2}} N^{-\frac{1}{2}} + \left(\beta R + \frac{1}{2} Z^{-\frac{1}{2}} N^{\frac{1}{2}}\right) z^k\right)}{(1+\beta)}\right) \qquad (B5.27)$$

$$z^{k\,(Inclusive)} = \frac{\frac{1}{2}\theta Z^{\frac{1}{2}} N^{-\frac{1}{2}}}{1 - \frac{1}{2}\theta Z^{\frac{1}{2}} N^{-\frac{1}{2}}} \frac{\frac{1}{2} Z^{\frac{1}{2}} N^{-\frac{1}{2}} + Rl_1}{\frac{1}{2} Z^{-\frac{1}{2}} L^{\frac{1}{2}} - R} \qquad (B5.28)$$

$$z^n = \frac{\beta}{1+\beta}(l_1 - s) - \frac{Z}{N(1+\beta)} \qquad (B5.29)$$

$$z^{k,Exclusive} = \frac{\frac{1}{2}\theta Z^{-\frac{1}{2}} N^{-\frac{1}{2}} (N - N^n) z^k}{\left(1 - \frac{1}{2}\theta Z^{-\frac{1}{2}} N^{-\frac{1}{2}} (N - N^n) z^k\right)} \frac{\left(\frac{1}{2} Z^{\frac{1}{2}} N^{-\frac{1}{2}} + Rl_1\right)}{\left(\frac{1}{2} Z^{-\frac{1}{2}} N^{\frac{1}{2}} - R\right)} \qquad (B5.30)$$

(1) Inclusive Kantian baseline B5.7, B5.8, B5.9
(2) Exclusive Kantian baseline B5.7, B5.9, B5.10
(3) Inclusive Kantian change production function B5.11, B5.12, B5.13
(4) Exclusive Kantian change production function B5.11, B5.13, B5.14
(5) Inclusive Kantian change utility function c2 B5.19, B5.20, B5.21
(6) Exclusive Kantian change utility function c2 B5.19, B5.21, B5.22
(7) Inclusive Kantian change utility function c1 B5.27, B5.28, B5.29
(8) Exclusive Kantian change utility function c1 B5.27, B5.29, B5.30

Appendix B6: Simulation output tables

Table B1: Simulation 1 results (Exclusive Kantians)

Nn/N	k	zk	zn	Z/N	F(Z,L)
0.1	0.047111647	0	0.064909444	0.006490944	0.080566397
0.2	0.038852613	0	0.060965978	0.012193196	0.110422804
0.3	0.033074739	0	0.057474227	0.017242268	0.131309817
0.4	0.028607323	0	0.05436078	0.021744312	0.147459527
0.5	0.024979832	0	0.051567318	0.025783659	0.160572908
0.6	0.0219443	0	0.049046921	0.029428152	0.171546357
0.7	0.019350591	0	0.046761417	0.032732992	0.180922612
0.8	0.017099687	0	0.04467943	0.035743544	0.189059631
0.9	0.015122365	0	0.042774936	0.038497442	0.196207651
1	0.013368142	0	0.041026165	0.041026165	0.202549167

Table B2: Simulation 2 results (Inclusive Kantians)

Nn	k	zk	zn	Z/N	F(Z,L)
0.1	0.045425626	0.000514799	0.064609755	0.006924295	0.083212347
0.2	0.036359798	0.001122887	0.060420225	0.012982354	0.113940136
0.3	0.030001626	0.00176314	0.056767355	0.018264405	0.135145864
0.4	0.025102287	0.002409179	0.053577732	0.0228766	0.151250125
0.5	0.021152734	0.00304557	0.050784797	0.026915183	0.164058476
0.6	0.01788019	0.003662879	0.048330815	0.030463641	0.174538365
0.7	0.015116613	0.00425547	0.046166523	0.033593207	0.183284499
0.8	0.012749341	0.004820236	0.044250202	0.036364209	0.190694018
0.9	0.010698465	0.005355778	0.042546642	0.038827556	0.19704709
1	0.008904999	0.005861849	0.041026165	0.041026165	0.202549167

Table B3.1: Simulation 3 results (Exclusive Kantian with lower capital share)

Nn	k	zk	zn	Z/N	F(Z,L)
0.1	0.002019073	0	0.060965978	0.006096598	0.182682038
0.2	-0.01231049	0	0.05436078	0.010872156	0.221533066
0.3	-0.020982166	0	0.049046921	0.014714076	0.245044147
0.4	-0.027033319	0	0.04467943	0.017871772	0.261450337
0.5	-0.03156741	0	0.041026165	0.020513083	0.273743391
0.6	-0.035119405	0	0.03792517	0.022755102	0.283373736
0.7	-0.037990036	0	0.035260014	0.02468201	0.291156735
0.8	-0.040364733	0	0.032944846	0.026355877	0.297595131
0.9	-0.042365391	0	0.030914972	0.027823475	0.303019416
1	-0.044076036	0	0.02912072	0.02912072	0.307657402

Table B3.2: Simulation 3 results (Exclusive Kantian with lower capital share) where $k \geq 0$

Nn	k	zk	zn	Z/N	F(Z,L)
0.1	0.002019073	0	0.060965978	0.006096598	0.182682038
0.2	0	0	0.05436078	0.010872156	0.221533066
0.3	0	0	0.049046921	0.014714076	0.245044147
0.4	0	0	0.04467943	0.017871772	0.261450337
0.5	0	0	0.041026165	0.020513083	0.273743391
0.6	0	0	0.03792517	0.022755102	0.283373736
0.7	0	0	0.035260014	0.02468201	0.291156735
0.8	0	0	0.032944846	0.026355877	0.297595131
0.9	0	0	0.030914972	0.027823475	0.303019416
1	0	0	0.02912072	0.02912072	0.307657402

Table B4.1: Simulation 4 results (Inclusive Kantian with lower capital share)

Nn	k	zk	zn	Z/N	F(Z,L)
0.1	-0.001216118	0.000559214	0.060354445	0.006538737	0.186995554
0.2	-0.016340404	0.001136822	0.053375452	0.011584548	0.226269682
0.3	-0.02539398	0.001667587	0.047905855	0.015539067	0.249540848
0.4	-0.031624869	0.002141901	0.043535049	0.01869916	0.265424311
0.5	-0.03622601	0.002561978	0.03997875	0.021270364	0.277071363
0.6	-0.039778909	0.002933413	0.037038273	0.023396329	0.286010892
0.7	-0.042610823	0.003262397	0.034572228	0.025179279	0.293099063
0.8	-0.044923103	0.003554741	0.032478038	0.026693379	0.298860039
0.9	-0.046847522	0.003815568	0.030679879	0.027993448	0.303635209
1	-0.048474364	0.004049273	0.02912072	0.02912072	0.307657402

Table B4.2: Simulation 4 results (Inclusive Kantian with lower capital share) where $k \geq 0$

Nn	k	zk	zn	Z/N	F(Z,L)
0.1	0	0.000559214	0.060354445	0.006538737	0.186995554
0.2	0	0.001136822	0.053375452	0.011584548	0.226269682
0.3	0	0.001667587	0.047905855	0.015539067	0.249540848
0.4	0	0.002141901	0.043535049	0.01869916	0.265424311
0.5	0	0.002561978	0.03997875	0.021270364	0.277071363
0.6	0	0.002933413	0.037038273	0.023396329	0.286010892
0.7	0	0.003262397	0.034572228	0.025179279	0.293099063
0.8	0	0.003554741	0.032478038	0.026693379	0.298860039
0.9	0	0.003815568	0.030679879	0.027993448	0.303635209
1	0	0.004049273	0.02912072	0.02912072	0.307657402

Table B5: Simulation 5 results (Exclusive Kantian with Stone Geary term in period 2)

Nn	k	zk	zn	Z/N	F(Z,L)
0.1	0.054337662	0	0.066331822	0.006633182	0.081444351
0.2	0.045864363	0	0.062804395	0.012560879	0.112075327
0.3	0.039896296	0	0.059540978	0.017862293	0.133649891
0.4	0.035258981	0	0.056560765	0.022624306	0.150413783
0.5	0.031478832	0	0.053843851	0.026921925	0.164079022
0.6	0.028305401	0	0.051363576	0.030818146	0.175550977
0.7	0.025586519	0	0.04909378	0.034365646	0.185379735
0.8	0.023221488	0	0.047010726	0.037608581	0.19392932
0.9	0.02113969	0	0.045093472	0.040584125	0.20145502
1	0.01928947	0	0.043323743	0.043323743	0.208143564

Table B6: Simulation 6 results (Inclusive Kantian with Stone Geary term in period 2)

Nn	k	zk	zn	Z/N	F(Z,L)
0.1	0.052860711	0.000452308	0.066109189	0.007017997	0.083773484
0.2	0.043643337	0.001006763	0.062366888	0.013278788	0.115233622
0.3	0.037123529	0.001605538	0.058951369	0.018809288	0.137146956
0.4	0.032064088	0.002222434	0.055889598	0.0236893	0.153913287
0.5	0.02796044	0.002841138	0.053158993	0.028000066	0.167332201
0.6	0.024541845	0.003450872	0.050726126	0.031816024	0.178370469
0.7	0.021641155	0.004044493	0.048556624	0.035202985	0.187624585
0.8	0.019145969	0.004617396	0.046618378	0.038218182	0.195494711
0.9	0.016976263	0.005166797	0.044882551	0.040910976	0.202264618
1	0.015072716	0.005691212	0.043323743	0.043323743	0.208143564

Table B7: Simulation 7 results (Exclusive Kantian with Stone Geary term in period 1)

Nn	k	zk	zn	Z/N	F(Z,L)
0.1	0.043626689	0	0.061014877	0.006101488	0.07811202
0.2	0.035619259	0	0.057308019	0.011461604	0.10705888
0.3	0.030017402	0	0.054025773	0.016207732	0.127309591
0.4	0.025686081	0	0.051099133	0.020439653	0.142967316
0.5	0.022169098	0	0.048473279	0.024236639	0.15568121
0.6	0.019226041	0	0.046104106	0.027662463	0.166320364
0.7	0.016711347	0	0.043955732	0.030769012	0.175410981
0.8	0.014529014	0	0.041998664	0.033598931	0.183300113
0.9	0.012611929	0	0.04020844	0.036187596	0.190230376
1	0.010911147	0	0.038564595	0.038564595	0.196378704

Table B8: Simulation 8 results (Inclusive Kantian with Stone Geary term in period 1)

Nn	k	zk	zn	Z/N	F(Z,L)
0.1	0.0420128	0.00047761	0.060736838	0.006503533	0.080644483
0.2	0.033246739	0.001035664	0.056804659	0.012189463	0.110405902
0.3	0.027105444	0.001618912	0.053376725	0.017146256	0.130943713
0.4	0.022376833	0.002204067	0.050382752	0.021475541	0.146545354
0.5	0.018566753	0.002777864	0.047759542	0.025268703	0.158961325
0.6	0.015410504	0.003332447	0.045452601	0.028604539	0.169128765
0.7	0.012745168	0.003863309	0.04341566	0.031549955	0.17762307
0.8	0.010461649	0.004368127	0.041609695	0.034161381	0.184827978
0.9	0.008482679	0.00484602	0.040001875	0.036486289	0.191013846
1	0.006751308	0.005297053	0.038564595	0.038564595	0.196378704

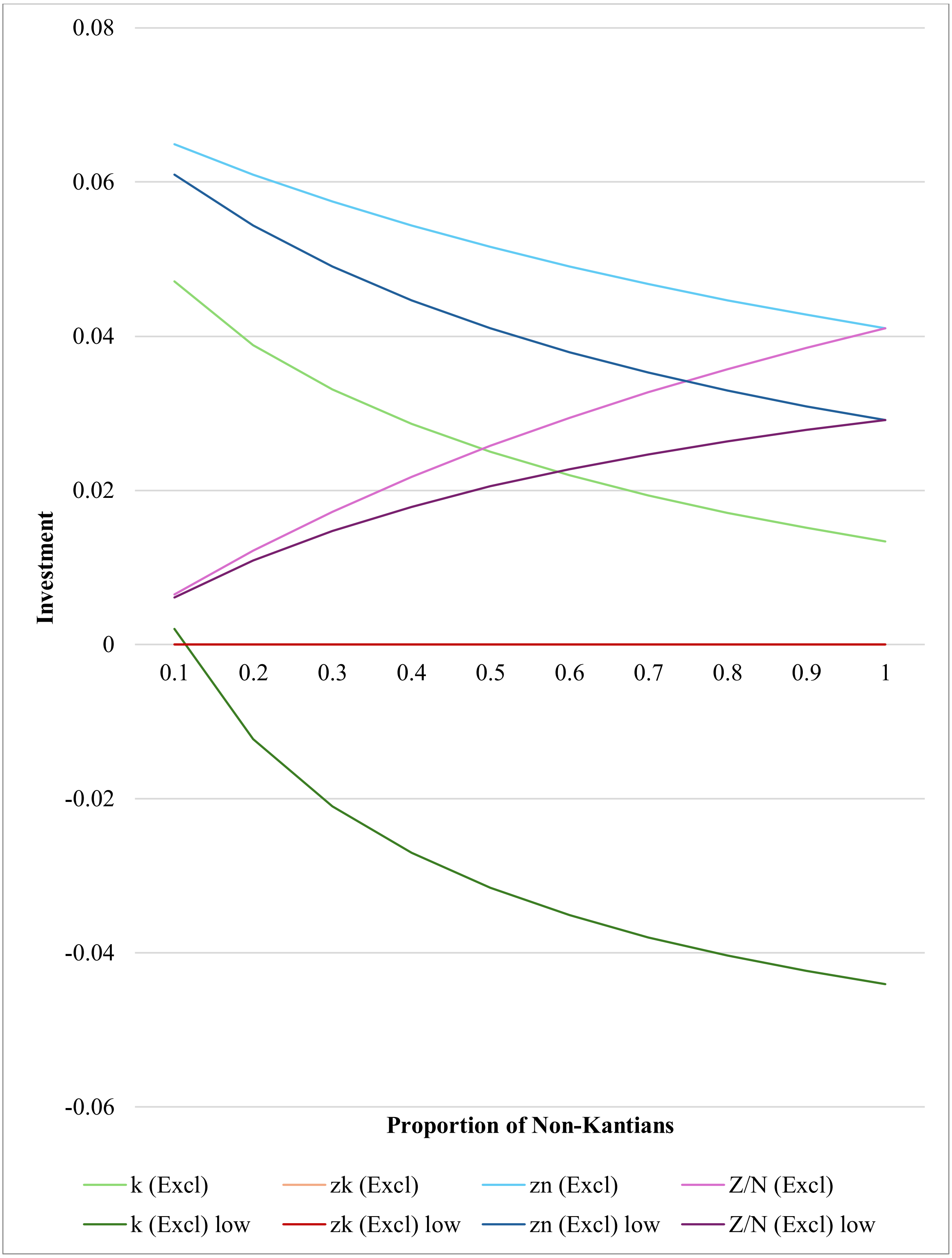


Figure B1: Graph to show difference between investment portfolios in the Exclusive Kantian equilibrium for different capital shares.

**Light coloured lines show equilibria for capital share=1/2, dark coloured lines show equilibria for capital share=1/3.*

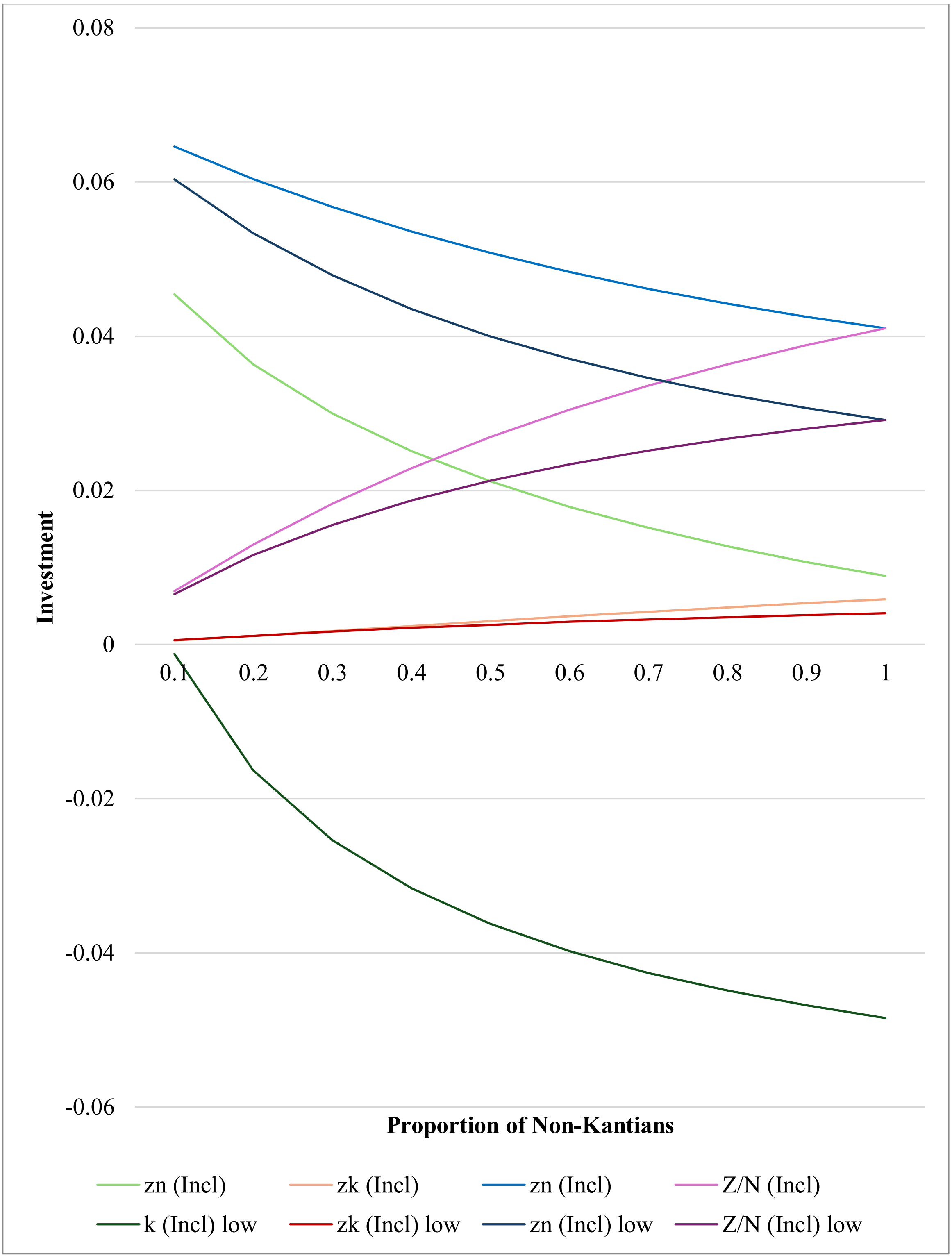


Figure B2: Graph to show difference between investment portfolios in the Inclusive Kantian equilibrium for different capital shares.

**Light coloured lines show equilibria for capital share=1/2, dark coloured lines show equilibria for capital share=1/3.*

Appendix B7: Simulation Maple code

Appendix B7.1: Inclusive Kantians

Inclusive Kantinas

$$> k=\frac{1}{R}\cdot\left(\frac{\text{beta}}{1+\text{beta}}\cdot R\cdot l1-\frac{\left(\frac{1}{2}\cdot((1-Nn)\cdot zk+Nn\cdot zn)^{\frac{1}{2}}\cdot N^{-\frac{1}{2}}+zk\cdot\left(\text{beta}\cdot R\cdot\left(\frac{1}{2}\right)\cdot((1-Nn)\cdot zk+Nn\cdot zn)^{-\frac{1}{2}}\cdot N^{\frac{1}{2}}\right)\right)}{1+\text{beta}}\right)$$

$$k=\frac{\frac{\beta R\,l1}{1+\beta}-\frac{\frac{\sqrt{(1-Nn)\,zk+Nn\,zn}}{2\sqrt{N}}+\frac{zk\,\beta\,R\sqrt{N}}{2\sqrt{(1-Nn)\,zk+Nn\,zn}}}{1+\beta}}{R} \quad \textbf{(1.1)}$$

$$> zk=\left(\frac{\left(\frac{1}{2}\cdot\text{theta}\cdot\left(\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}\right)^{\frac{1}{2}}\right)}{\left(1-\frac{1}{2}\cdot\text{theta}\cdot\left(\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}\right)^{\frac{1}{2}}\right)}\right)\cdot\left(\frac{\left(\frac{1}{2}\cdot\left(\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}\right)^{\frac{1}{2}}+R\cdot l1\right)}{\left(\frac{1}{2}\cdot\left(\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}\right)^{\frac{-1}{2}}-R\right)}\right)$$

$$zk=\frac{\theta\sqrt{\frac{(1-Nn)\,zk+Nn\,zn}{N}}\left(\frac{\sqrt{\frac{(1-Nn)\,zk+Nn\,zn}{N}}}{2}+R\,l1\right)}{2\left(1-\frac{\theta\sqrt{\frac{(1-Nn)\,zk+Nn\,zn}{N}}}{2}\right)\left(\frac{1}{2\sqrt{\frac{(1-Nn)\,zk+Nn\,zn}{N}}}-R\right)} \quad \textbf{(1.2)}$$

$$> zn=\frac{\text{beta}}{1+\text{beta}}\cdot l1-\frac{1}{1+\text{beta}}\cdot\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}$$

$$zn=\frac{\beta\,l1}{1+\beta}-\frac{(1-Nn)\,zk+Nn\,zn}{(1+\beta)\,N} \quad \textbf{(1.3)}$$

$$> eval(\{\mathbf{(1.1)},\mathbf{(1.2)},\mathbf{(1.3)}\},\{\text{beta}=0.446, R=1.25, l1=0.225, \text{theta}=0.181, N=1, Nn=1\})$$

$$\left\{k=0.06939834026-0.2766251729\sqrt{zn}-\frac{0.1542185339\,zk}{\sqrt{zn}},\ zk=\frac{0.09050000000\sqrt{zn}\left(\frac{\sqrt{zn}}{2}+0.28125\right)}{\left(1-0.09050000000\sqrt{zn}\right)\left(\frac{1}{2\sqrt{zn}}-1.25\right)},\ zn=0.06939834026-0.6915629322\,zn\right\} \quad \textbf{(1.4)}$$

$$> solve(\mathbf{(1.4)},\{zn, zk, k\})$$

$$\{k=0.008904999159,\ zk=0.005861849478,\ zn=0.04102616517\} \quad \textbf{(1.5)}$$

Appendix B7.2: Exclusive Kantians

Exclusive Kantians

$$> k=\frac{1}{R}\cdot\left(\frac{\text{beta}}{1+\text{beta}}\cdot R\cdot l1-\frac{\left(\frac{1}{2}\cdot((1-Nn)\cdot zk+Nn\cdot zn)^{\frac{1}{2}}\cdot N^{-\frac{1}{2}}+zk\cdot\left(\text{beta}\cdot R\cdot\left(\frac{1}{2}\right)\cdot((1-Nn)\cdot zk+Nn\cdot zn)^{-\frac{1}{2}}\cdot N^{\frac{1}{2}}\right)\right)}{1+\text{beta}}\right)$$

$$k=\frac{\frac{\beta R\,l1}{1+\beta}-\frac{\frac{\sqrt{(1-Nn)\,zk+Nn\,zn}}{2\sqrt{N}}+\frac{zk\,\beta\,R\sqrt{N}}{2\sqrt{(1-Nn)\,zk+Nn\,zn}}}{1+\beta}}{R} \quad \textbf{(2.1)}$$

$$> zk=\left(\frac{\left(\frac{1}{2}\cdot\text{theta}\cdot(((1-Nn)\cdot zk+Nn\cdot zn))^{-\frac{1}{2}}\cdot N^{-\frac{1}{2}}\cdot(N-Nn)\cdot zk\right)}{\left(1-\frac{1}{2}\cdot\text{theta}\cdot(((1-Nn)\cdot zk+Nn\cdot zn))^{-\frac{1}{2}}\cdot N^{-\frac{1.}{2}}\cdot(N-Nn)\cdot zk\right)}\right)\cdot\left(\frac{\left(\frac{1}{2}\cdot\left(\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}\right)^{\frac{1}{2}}+R\cdot l1\right)}{\left(\frac{1}{2}\cdot\left(\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}\right)^{\frac{-1}{2}}-R\right)}\right)$$

$$zk=\frac{\theta\,(N-Nn)\,zk\left(\frac{\sqrt{\frac{(1-Nn)\,zk+Nn\,zn}{N}}}{2}+R\,l1\right)}{2\sqrt{(1-Nn)\,zk+Nn\,zn}\,\sqrt{N}\left(1-\frac{\theta\,(N-Nn)\,zk}{2\sqrt{(1-Nn)\,zk+Nn\,zn}\,\sqrt{N}}\right)\left(\frac{1}{2\sqrt{\frac{(1-Nn)\,zk+Nn\,zn}{N}}}-R\right)} \quad \textbf{(2.2)}$$

$$> zn=\frac{\text{beta}}{1+\text{beta}}\cdot l1-\frac{1}{1+\text{beta}}\cdot\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}$$

$$zn=\frac{\beta\,l1}{1+\beta}-\frac{(1-Nn)\,zk+Nn\,zn}{(1+\beta)\,N} \quad \textbf{(2.3)}$$

$$> eval(\{\mathbf{(2.1)},\mathbf{(2.2)},\mathbf{(2.3)}\},\{\text{beta}=0.446, R=1.25, l1=0.225, \text{theta}=0.181, N=1, Nn=1\})$$

$$\left\{k=0.06939834026-0.2766251729\sqrt{zn}-\frac{0.1542185339\,zk}{\sqrt{zn}},\ zk=0.,\ zn=0.06939834026-0.6915629322\,zn\right\} \quad \textbf{(2.4)}$$

$$> solve(\mathbf{(2.4)},\{zn, zk, k\})$$

$$\{k=0.01336814183,\ zk=0.,\ zn=0.04102616517\} \quad \textbf{(2.5)}$$

Appendix B7.3: Inclusive Kantians with lower capital share in production

Inclusive Kantians with Production Function F(Z,L)=Z^(1/3) L^(2/3)

> $$k=\frac{1}{R}\cdot\left(\frac{\mathrm{beta}}{1+\mathrm{beta}}\cdot R\cdot I1-\frac{\left(\frac{2}{3}\cdot((1-Nn)\cdot zk+Nn\cdot zn)^{\frac{1}{3}}\cdot N^{-\frac{1}{3}}+zk\cdot\left(\mathrm{beta}\cdot R\cdot\left(\frac{1}{3}\right)\cdot((1-Nn)\cdot zk+Nn\cdot zn)^{-\frac{2}{3}}\cdot N^{\frac{2}{3}}\right)\right)}{1+\mathrm{beta}}\right)$$

$$k=\frac{\frac{\beta R I1}{1+\beta}-\frac{\frac{2((1-Nn)zk+Nn\,zn)^{1/3}}{3N^{1/3}}+\frac{zk\,\beta R N^{2/3}}{3((1-Nn)zk+Nn\,zn)^{2/3}}}{1+\beta}}{R} \tag{3.1}$$

> $$zk=\left(\frac{\left(\frac{1}{3}\cdot\mathrm{theta}\cdot\left(\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}\right)^{\frac{1}{3}}\right)}{\left(1-\frac{1}{3}\cdot\mathrm{theta}\cdot\left(\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}\right)^{\frac{1}{3}}\right)}\right)\cdot\left(\frac{\left(\frac{2}{3}\cdot\left(\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}\right)^{\frac{1}{3}}+R\cdot I1\right)}{\left(\frac{1}{3}\cdot\left(\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}\right)^{\frac{-2}{3}}-R\right)}\right)$$

$$zk=\frac{\theta\left(\frac{(1-Nn)zk+Nn\,zn}{N}\right)^{1/3}\left(\frac{2\left(\frac{(1-Nn)zk+Nn\,zn}{N}\right)^{1/3}}{3}+R\,I1\right)}{3\left(1-\frac{\theta\left(\frac{(1-Nn)zk+Nn\,zn}{N}\right)^{1/3}}{3}\right)\left(\frac{1}{3\left(\frac{(1-Nn)zk+Nn\,zn}{N}\right)^{2/3}}-R\right)} \tag{3.2}$$

> $$zn=\frac{\mathrm{beta}}{1+\mathrm{beta}}\cdot I1-\frac{1}{1+\mathrm{beta}}\cdot\frac{2\cdot((1-Nn)\cdot zk+Nn\cdot zn)}{N}$$

$$zn=\frac{\beta I1}{1+\beta}-\frac{2((1-Nn)zk+Nn\,zn)}{(1+\beta)N} \tag{3.3}$$

> $eval(\{\mathbf{(3.1)}, \mathbf{(3.2)}, \mathbf{(3.3)}\}, \{\mathrm{beta}=0.446, R=1.25, I1=0.225, \mathrm{theta}=0.181, N=1, Nn=1\})$

$$\left\{k=0.06939834026-0.3688335638\,zn^{1/3}-\frac{0.1028123559\,zk}{zn^{2/3}},\ zk=\frac{0.06033333333\,zn^{1/3}\left(\frac{2\,zn^{1/3}}{3}+0.28125\right)}{(1-0.06033333333\,zn^{1/3})\left(\frac{1}{3\,zn^{2/3}}-1.25\right)},\ zn=0.06939834026-1.383125864\,zn\right\} \tag{3.4}$$

> $solve(\mathbf{(3.4)}, \{zn, zk, k\})$

$$\{k=-0.04847436435,\ zk=0.004049273462,\ zn=0.02912071969\} \tag{3.5}$$

Appendix B7.4: Exclusive Kantians with lower capital share in production

Exclusive Kantians with Production Function F(Z,L)=Z^(1/3) L^(2/3)

> $$k=\frac{1}{R}\cdot\left(\frac{\mathrm{beta}}{1+\mathrm{beta}}\cdot R\cdot I1-\frac{\left(\frac{2}{3}\cdot((1-Nn)\cdot zk+Nn\cdot zn)^{\frac{1}{3}}\cdot N^{-\frac{1}{3}}+zk\cdot\left(\mathrm{beta}\cdot R\cdot\left(\frac{1}{3}\right)\cdot((1-Nn)\cdot zk+Nn\cdot zn)^{-\frac{2}{3}}\cdot N^{\frac{2}{3}}\right)\right)}{1+\mathrm{beta}}\right)$$

$$k=\frac{\frac{\beta R I1}{1+\beta}-\frac{\frac{2((1-Nn)zk+Nn\,zn)^{1/3}}{3N^{1/3}}+\frac{zk\,\beta R N^{2/3}}{3((1-Nn)zk+Nn\,zn)^{2/3}}}{1+\beta}}{R} \tag{4.1}$$

> $$zk=\left(\frac{\left(\frac{1}{3}\cdot\mathrm{theta}\cdot(((1-Nn)\cdot zk+Nn\cdot zn))^{-\frac{2}{3}}\cdot N^{-\frac{1}{3}}\cdot(N-Nn)\cdot zk\right)}{\left(1-\frac{1}{3}\cdot\mathrm{theta}\cdot(((1-Nn)\cdot zk+Nn\cdot zn))^{-\frac{2}{3}}\cdot N^{-\frac{1}{3}}\cdot(N-Nn)\cdot zk\right)}\right)\cdot\left(\frac{\left(\frac{2}{3}\cdot\left(\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}\right)^{\frac{1}{3}}+R\cdot I1\right)}{\left(\frac{1}{3}\cdot\left(\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}\right)^{\frac{-2}{3}}-R\right)}\right)$$

$$zk=\frac{\theta(N-Nn)zk\left(\frac{2\left(\frac{(1-Nn)zk+Nn\,zn}{N}\right)^{1/3}}{3}+R\,I1\right)}{3((1-Nn)zk+Nn\,zn)^{2/3}N^{1/3}\left(1-\frac{\theta(N-Nn)zk}{3((1-Nn)zk+Nn\,zn)^{2/3}N^{1/3}}\right)\left(\frac{1}{3\left(\frac{(1-Nn)zk+Nn\,zn}{N}\right)^{2/3}}-R\right)} \tag{4.2}$$

> $$zn=\frac{\mathrm{beta}}{1+\mathrm{beta}}\cdot I1-\frac{1}{1+\mathrm{beta}}\cdot\frac{2\cdot((1-Nn)\cdot zk+Nn\cdot zn)}{N}$$

$$zn=\frac{\beta I1}{1+\beta}-\frac{2((1-Nn)zk+Nn\,zn)}{(1+\beta)N} \tag{4.3}$$

> $eval(\{\mathbf{(4.1)}, \mathbf{(4.2)}, \mathbf{(4.3)}\}, \{\mathrm{beta}=0.446, R=1.25, I1=0.225, \mathrm{theta}=0.181, N=1, Nn=1\})$

$$\left\{k=0.06939834026-0.3688335638\,zn^{1/3}-\frac{0.1028123559\,zk}{zn^{2/3}},\ zk=0.,\ zn=0.06939834026-1.383125864\,zn\right\} \tag{4.4}$$

> $solve(\mathbf{(4.4)}, \{zn, zk, k\})$

$$\{k=-0.04407603565,\ zk=0.,\ zn=0.02912071969\} \tag{4.5}$$

Appendix B7.5: Inclusive Kantians with Stone Geary term in period 2

Inclusive Kantians with Stone Geary in Period 2

$$> k=\frac{1}{R}\cdot\left(\frac{\text{beta}}{1+\text{beta}}\cdot R\cdot I1-\frac{\left(\frac{1}{2}\cdot((1-Nn)\cdot zk+Nn\cdot zn)^{\frac{1}{2}}\cdot N^{-\frac{1}{2}}+zk\cdot\left(\text{beta}\cdot R\cdot\left(\frac{1}{2}\right)\cdot((1-Nn)\cdot zk+Nn\cdot zn)^{-\frac{1}{2}}\cdot N^{\frac{1}{2}}\right)\right)}{1+\text{beta}}+\frac{0.0135}{(1+\text{beta})}\right)$$

$$k=\frac{\frac{\beta R\,I1}{1+\beta}-\frac{\frac{\sqrt{(1-Nn)\,zk+Nn\,zn}}{2\sqrt{N}}+\frac{zk\,\beta\,R\sqrt{N}}{2\sqrt{(1-Nn)\,zk+Nn\,zn}}}{1+\beta}+\frac{0.0135}{1+\beta}}{R} \quad (1)$$

$$> zk=\left(\frac{\left(\frac{1}{2}\cdot\text{theta}\cdot\left(\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}\right)^{\frac{1}{2}}\right)}{\left(1-\frac{1}{2}\cdot\text{theta}\cdot\left(\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}\right)^{\frac{1}{2}}\right)}\right)\cdot\left(\frac{\left(\frac{1}{2}\cdot\left(\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}\right)^{\frac{1}{2}}+R\cdot I1-\frac{(1+\text{beta})}{\text{beta}}\cdot 0.0135\right)}{\left(\frac{1}{2}\cdot\left(\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}\right)^{\frac{-1}{2}}-R\right)}\right)$$

$$zk=\frac{\theta\sqrt{\frac{(1-Nn)\,zk+Nn\,zn}{N}}\left(\frac{\sqrt{\frac{(1-Nn)\,zk+Nn\,zn}{N}}}{2}+R\,I1-\frac{0.0135\,(1+\beta)}{\beta}\right)}{2\left(1-\frac{\theta\sqrt{\frac{(1-Nn)\,zk+Nn\,zn}{N}}}{2}\right)\left(\frac{1}{2\sqrt{\frac{(1-Nn)\,zk+Nn\,zn}{N}}}-R\right)} \quad (2)$$

$$> zn=\frac{\text{beta}}{1+\text{beta}}\cdot I1-\frac{1}{1+\text{beta}}\cdot\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}+\frac{0.0135}{(1+\text{beta})\cdot 0.5\cdot((1-Nn)\cdot zk+Nn\cdot zn)^{-\frac{1}{2}}\cdot N^{\frac{1}{2}}}$$

$$zn=\frac{\beta\,I1}{1+\beta}-\frac{(1-Nn)\,zk+Nn\,zn}{(1+\beta)\,N}+\frac{0.02700000000\sqrt{(1-Nn)\,zk+Nn\,zn}}{(1+\beta)\sqrt{N}} \quad (3)$$

$> eval(\{(1), (2), (3)\}, \{\text{beta}=0.446, R=1.25, I1=0.225, \text{theta}=0.181, N=1, Nn=1\})$

$$\left\{k=0.07686721994-0.2766251729\sqrt{zn}-\frac{0.1542185339\,zk}{\sqrt{zn}},\ zk=\frac{0.09050000000\sqrt{zn}\left(\frac{\sqrt{zn}}{2}+0.2374809417\right)}{\left(1-0.09050000000\sqrt{zn}\right)\left(\frac{1}{2\sqrt{zn}}-1.25\right)},\ zn=0.06939834026-0.6915629322\,zn+0.01867219917\sqrt{zn}\right\} \quad (4)$$

$> solve((4), \{zn, zk, k\})$

$$\{k=0.01507271577, zk=0.005691211903, zn=0.04332374336\} \quad (5)$$

Appendix B7.6: Exclusive Kantians with Stone Geary term in period 2

Exclusive Kantians with Stone Geary in Period 2

$$> k=\frac{1}{R}\cdot\left(\frac{\text{beta}}{1+\text{beta}}\cdot R\cdot I1-\frac{\left(\frac{1}{2}\cdot((1-Nn)\cdot zk+Nn\cdot zn)^{\frac{1}{2}}\cdot N^{-\frac{1}{2}}+zk\cdot\left(\text{beta}\cdot R\cdot\left(\frac{1}{2}\right)\cdot((1-Nn)\cdot zk+Nn\cdot zn)^{-\frac{1}{2}}\cdot N^{\frac{1}{2}}\right)\right)}{1+\text{beta}}+\frac{0.0135}{1+\text{beta}}\right)$$

$$k=\frac{\frac{\beta R\,I1}{1+\beta}-\frac{\frac{\sqrt{(1-Nn)\,zk+Nn\,zn}}{2\sqrt{N}}+\frac{zk\,\beta\,R\sqrt{N}}{2\sqrt{(1-Nn)\,zk+Nn\,zn}}}{1+\beta}+\frac{0.0135}{1+\beta}}{R} \quad (6.1)$$

$$> zk=\left(\frac{\left(\frac{1}{2}\cdot\text{theta}\cdot(((1-Nn)\cdot zk+Nn\cdot zn))^{-\frac{1}{2}}\cdot N^{-\frac{1}{2}}\cdot(N-Nn)\cdot zk\right)}{\left(1-\frac{1}{2}\cdot\text{theta}\cdot(((1-Nn)\cdot zk+Nn\cdot zn))^{-\frac{1}{2}}\cdot N^{-\frac{1.}{2}}\cdot(N-Nn)\cdot zk\right)}\right)\cdot\left(\frac{\left(\frac{1}{2}\cdot\left(\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}\right)^{\frac{1}{2}}+R\cdot I1-\left(\frac{1+\text{beta}}{\text{beta}}\cdot 0.0135\right)\right)}{\left(\frac{1}{2}\cdot\left(\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}\right)^{\frac{-1}{2}}-R\right)}\right)$$

$$zk=\frac{\theta\,(N-Nn)\,zk\left(\frac{\sqrt{\frac{(1-Nn)\,zk+Nn\,zn}{N}}}{2}+R\,I1-\frac{0.0135\,(1+\beta)}{\beta}\right)}{2\sqrt{(1-Nn)\,zk+Nn\,zn}\sqrt{N}\left(1-\frac{\theta\,(N-Nn)\,zk}{2\sqrt{(1-Nn)\,zk+Nn\,zn}\sqrt{N}}\right)\left(\frac{1}{2\sqrt{\frac{(1-Nn)\,zk+Nn\,zn}{N}}}-R\right)} \quad (6.2)$$

$$> zn=\frac{\text{beta}}{1+\text{beta}}\cdot I1-\frac{1}{1+\text{beta}}\cdot\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}+\frac{0.0135}{(1+\text{beta})\cdot 0.5\cdot((1-Nn)\cdot zk+Nn\cdot zn)^{-\frac{1}{2}}\cdot N^{\frac{1}{2}}}$$

$$zn=\frac{\beta\,I1}{1+\beta}-\frac{(1-Nn)\,zk+Nn\,zn}{(1+\beta)\,N}+\frac{0.02700000000\sqrt{(1-Nn)\,zk+Nn\,zn}}{(1+\beta)\sqrt{N}} \quad (6.3)$$

$> eval(\{(6.1), (6.2), (6.3)\}, \{\text{beta}=0.446, R=1.25, I1=0.225, \text{theta}=0.181, N=1, Nn=1\})$

$$\left\{k=0.07686721994-0.2766251729\sqrt{zn}-\frac{0.1542185339\,zk}{\sqrt{zn}},\ zk=0.,\ zn=0.06939834026-0.6915629322\,zn+0.01867219917\sqrt{zn}\right\} \quad (6.4)$$

$> solve((6.4), \{zn, zk, k\})$

$$\{k=0.01928947048, zk=0., zn=0.04332374336\} \quad (6.5)$$

Appendix B7.7: Inclusive Kantians with Stone Geary term in period 1

Inclusive Kantinas with Stone Geary term in Period 1

$$> \ k=\frac{1}{R}\cdot\left(\frac{\text{beta}}{1+\text{beta}}\cdot R\cdot(I1-0.0135)-\frac{\left(\frac{1}{2}\cdot((1-Nn)\cdot zk+Nn\cdot zn)^{\frac{1}{2}}\cdot N^{-\frac{1}{2}}+zk\cdot\left(\text{beta}\cdot R\cdot\left(\frac{1}{2}\right)\cdot((1-Nn)\cdot zk+Nn\cdot zn)^{-\frac{1}{2}}\cdot N^{\frac{1}{2}}\right)\right)}{1+\text{beta}}\right)$$

$$k=\frac{\frac{\beta R\,(I1-0.0135)}{1+\beta}-\frac{\frac{\sqrt{(1-Nn)\,zk+Nn\,zn}}{2\sqrt{N}}+\frac{zk\,\beta\,R\sqrt{N}}{2\sqrt{(1-Nn)\,zk+Nn\,zn}}}{1+\beta}}{R} \tag{7.1}$$

$$> \ zk=\left(\frac{\left(\frac{1}{2}\cdot\text{theta}\cdot\left(\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}\right)^{\frac{1}{2}}\right)}{\left(1-\frac{1}{2}\cdot\text{theta}\cdot\left(\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}\right)^{\frac{1}{2}}\right)}\right)\cdot\left(\frac{\left(\frac{1}{2}\cdot\left(\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}\right)^{\frac{1}{2}}+R\cdot I1\right)}{\left(\frac{1}{2}\cdot\left(\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}\right)^{\frac{-1}{2}}-R\right)}\right)$$

$$zk=\frac{\theta\sqrt{\frac{(1-Nn)\,zk+Nn\,zn}{N}}\left(\frac{\sqrt{\frac{(1-Nn)\,zk+Nn\,zn}{N}}}{2}+R\,I1\right)}{2\left(1-\frac{\theta\sqrt{\frac{(1-Nn)\,zk+Nn\,zn}{N}}}{2}\right)\left(\frac{1}{2\sqrt{\frac{(1-Nn)\,zk+Nn\,zn}{N}}}-R\right)} \tag{7.2}$$

$$> \ zn=\frac{\text{beta}}{1+\text{beta}}\cdot(I1-0.0135)-\frac{1}{1+\text{beta}}\cdot\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}$$

$$zn=\frac{\beta\,(I1-0.0135)}{1+\beta}-\frac{(1-Nn)\,zk+Nn\,zn}{(1+\beta)\,N} \tag{7.3}$$

$$> \ eval(\{(7.1),(7.2),(7.3)\},\{\text{beta}=0.446,R=1.25,I1=0.225,\text{theta}=0.181,N=1,Nn=1\})$$

$$\left\{k=0.06523443985-0.2766251729\sqrt{zn}-\frac{0.1542185339\,zk}{\sqrt{zn}},\ zk=\frac{0.09050000000\sqrt{zn}\left(\frac{\sqrt{zn}}{2}+0.28125\right)}{\left(1-0.09050000000\sqrt{zn}\right)\left(\frac{1}{2\sqrt{zn}}-1.25\right)},\ zn=0.06523443984-0.6915629322\,zn\right\} \tag{7.4}$$

$$> \ solve((7.4),\{zn,zk,k\})$$

$$\{k=0.006751308132,\ zk=0.005297053095,\ zn=0.03856459526\} \tag{7.5}$$

Appendix B7.8: Exclusive Kantians with Stone Geary term in period 1

Exclusive Kantians

$$> \ k=\frac{1}{R}\cdot\left(\frac{\text{beta}}{1+\text{beta}}\cdot R\cdot(I1-0.0135)-\frac{\left(\frac{1}{2}\cdot((1-Nn)\cdot zk+Nn\cdot zn)^{\frac{1}{2}}\cdot N^{-\frac{1}{2}}+zk\cdot\left(\text{beta}\cdot R\cdot\left(\frac{1}{2}\right)\cdot((1-Nn)\cdot zk+Nn\cdot zn)^{-\frac{1}{2}}\cdot N^{\frac{1}{2}}\right)\right)}{1+\text{beta}}\right)$$

$$k=\frac{\frac{\beta R\,(I1-0.0135)}{1+\beta}-\frac{\frac{\sqrt{(1-Nn)\,zk+Nn\,zn}}{2\sqrt{N}}+\frac{zk\,\beta\,R\sqrt{N}}{2\sqrt{(1-Nn)\,zk+Nn\,zn}}}{1+\beta}}{R} \tag{8.1}$$

$$> \ zk=\left(\frac{\left(\frac{1}{2}\cdot\text{theta}\cdot(((1-Nn)\cdot zk+Nn\cdot zn))^{-\frac{1}{2}}\cdot N^{-\frac{1}{2}}\cdot(N-Nn)\cdot zk\right)}{\left(1-\frac{1}{2}\cdot\text{theta}\cdot(((1-Nn)\cdot zk+Nn\cdot zn))^{-\frac{1}{2}}\cdot N^{-\frac{1.}{2}}\cdot(N-Nn)\cdot zk\right)}\right)\cdot\left(\frac{\left(\frac{1}{2}\cdot\left(\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}\right)^{\frac{1}{2}}+R\cdot I1\right)}{\left(\frac{1}{2}\cdot\left(\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}\right)^{\frac{-1}{2}}-R\right)}\right)$$

$$zk=\frac{\theta\,(N-Nn)\,zk\left(\frac{\sqrt{\frac{(1-Nn)\,zk+Nn\,zn}{N}}}{2}+R\,I1\right)}{2\sqrt{(1-Nn)\,zk+Nn\,zn}\,\sqrt{N}\left(1-\frac{\theta\,(N-Nn)\,zk}{2\sqrt{(1-Nn)\,zk+Nn\,zn}\,\sqrt{N}}\right)\left(\frac{1}{2\sqrt{\frac{(1-Nn)\,zk+Nn\,zn}{N}}}-R\right)} \tag{8.2}$$

$$> \ zn=\frac{\text{beta}}{1+\text{beta}}\cdot(I1-0.0135)-\frac{1}{1+\text{beta}}\cdot\frac{((1-Nn)\cdot zk+Nn\cdot zn)}{N}$$

$$zn=\frac{\beta\,(I1-0.0135)}{1+\beta}-\frac{(1-Nn)\,zk+Nn\,zn}{(1+\beta)\,N} \tag{8.3}$$

$$> \ eval(\{(8.1),(8.2),(8.3)\},\{\text{beta}=0.446,R=1.25,I1=0.225,\text{theta}=0.181,N=1,Nn=1\})$$

$$\left\{k=0.06523443985-0.2766251729\sqrt{zn}-\frac{0.1542185339\,zk}{\sqrt{zn}},\ zk=0.,\ zn=0.06523443984-0.6915629322\,zn\right\} \tag{8.4}$$

$$> \ solve((8.4),\{zn,zk,k\})$$

$$\{k=0.01091114699,\ zk=0.,\ zn=0.03856459526\} \tag{8.5}$$

Appendix C: Appendix for Chapter 3

Appendix C1: Survey questions

Dear Resident,

You are invited to participate in a survey which will inform Durham University's research project on Geothermal Energy from Mines and Solar Geothermal Heat (GEMS). The main purpose of this survey is to understand how households in the North East of England make decisions regarding their heating system.

The GEMS research project explores whether water from flooded, abandoned mines could be used as a low-carbon, geothermal source of heat for UK homes. It is expected that this geothermal energy system will contribute to reducing CO2 emissions and creating new jobs in the region. GEMS is an interdisciplinary project funded by the UK Engineering and Physical Sciences Research Council (EPSRC). For more information, please see: https://gems.ac.uk/

The survey should take no longer than 15 minutes. It comprises of 4 main sections:

1. About your preferences
2. Score cards
3. About you
4. About your accommodation.

Your response will be anonymous and no identifiable information will be collected. The results will be analysed by researchers at Durham University and reported to the research council.

For further information on the survey, you can contact Dr Laura Marsiliani on 0191 3346363 or at laura.marsiliani@durham.ac.uk

Thank you
The GEMS project team
June 2023

Survey Part 1: Behavioural Questions
Here are some questions about your energy preference. Please tick the box that describes you best.

Q1: I know how to adjust the thermostat/heating to reduce my energy usage.
A1: Strongly disagree / Disagree / Neither agree nor disagree / Agree / Strongly agree

Q2: I know other ways to reduce my energy usage (for example, only heating certain rooms or washing laundry at a low temperature) in the house.
A2: Strongly disagree / Disagree / Neither agree nor disagree / Agree / Strongly agree

Q3: In the past winter, I have adjusted my thermostat/heating and/or used other ways to save energy.
A3: Strongly disagree / Disagree / Neither agree nor disagree / Agree / Strongly agree

Q4: I am involved in energy-related decisions (heating, energy usage, etc.) in my household.
A4: Strongly disagree / Disagree / Neither agree nor disagree / Agree / Strongly agree

Q5: I support the UK government's ambition to ban the sale of gas boilers in the future.
A5: Strongly disagree / Disagree / Neither agree nor disagree / Agree / Strongly agree

Q6: Government financial support (grants) to households is necessary for households to invest in a low-carbon heating system.
A6: Strongly disagree / Disagree / Neither agree nor disagree / Agree / Strongly agree

Q7: I would be incentivised to switch to a low-carbon heating system if I was offered a government grant.
A7: Strongly disagree / Disagree / Neither agree nor disagree / Agree / Strongly agree

Q8: I would like to produce my own heating (for example, through a biomass boiler or a wood burner).
A8: Strongly disagree / Disagree / Neither agree nor disagree / Agree / Strongly agree

Q9: I would like a local community organisation to own, supply or manage the heating system in my neighbourhood.
A9: Strongly disagree / Disagree / Neither agree nor disagree / Agree / Strongly agree

Q10: The North East of England claims to have a 'proud mining heritage'. I personally identify with this heritage.
A10: Strongly disagree / Disagree / Neither agree nor disagree / Agree / Strongly agree

Q11: Using disused (abandoned) coal mines as a source of geothermal energy honours the history of coal mining.

A11: Strongly disagree / Disagree / Neither agree nor disagree / Agree / Strongly agree

Q12: Research projects like this one at Durham University are important for my community.
A12: Strongly disagree / Disagree / Neither agree nor disagree / Agree / Strongly agree

Q13: I know what 'carbon footprint' means.
A13: Strongly disagree / Disagree / Neither agree nor disagree / Agree / Strongly agree

Q14: I am concerned about damage to the natural environment caused by human activities.
A14: Strongly disagree / Disagree / Neither agree nor disagree / Agree / Strongly agree

Q15: I make changes to my lifestyle to protect the environment (for example, by recycling rather than throwing things away, using my car less, or buying local food).
A15: Strongly disagree / Disagree / Neither agree nor disagree / Agree / Strongly agree

Q16: What proportion of people in the North East of England do you think make changes in their lifestyles to protect the environment? (for example, by recycling rather than throwing things away, using their car less, or buying local food)
A16: Please provide your best guess in percentage on the slider scale from 0% to 100% (continuous slider from 0% to 100%).

Q17: I believe that people in the UK *should* make changes to their lifestyles to protect the environment.
A17: Strongly disagree / Disagree / Neither agree nor disagree / Agree / Strongly agree

Q18: What proportion of people in the North East of England do you think believe that people in the UK should make changes in their lifestyles to protect the environment? [
A18: Please provide your best guess in percentage on the slider scale from 0% to 100% (continuous slider from 0% to 100%).

Q19: I am willing to ask for advice from neighbours, colleagues and friends when I am making decisions relating to my heating usage/system.
A19: Strongly disagree / Disagree / Neither agree nor disagree / Agree / Strongly agree

Q20: I use the internet/social media for information when I am making decisions relating to my heating usage/system.
A20: Strongly disagree / Disagree / Neither agree nor disagree / Agree / Strongly agree

Survey Part 2: Choice experiment

In this section, you will be presented with several choice cards with low-carbon alternatives for domestic heat. You will be asked to make a choice based on five attributes of the heating systems. All of the heating systems in the choice cards give the **same** amount of heat.

Suppose you are selecting a **new** heating system for **new** residential accommodation. There are four heating systems available:

1. Geothermal district heating from disused mines;
2. Hydrogen boiler;
3. Solar electric boiler and
4. Air source heat pump.

Inside the building, the equipment needed for the operation of the four heating systems is similar and it is typically a heat exchanger. The diagram below shows an example of a heat exchanger:

Figure C1: Image of a heat exchanger used for all the heating systems (Source: Kensa Contracting)

Geothermal District Heating from disused mines: *For geothermal district heating from disused (abandoned) mines, warm groundwater is extracted from flooded coal mines. A district heat pump extracts the heat from this water. Then the hot water (red dotted line) is supplied to the household via underground pipes, and the cold water (blue dotted line) is returned to the mining system. The diagram below shows how a geothermal district heating system works:*

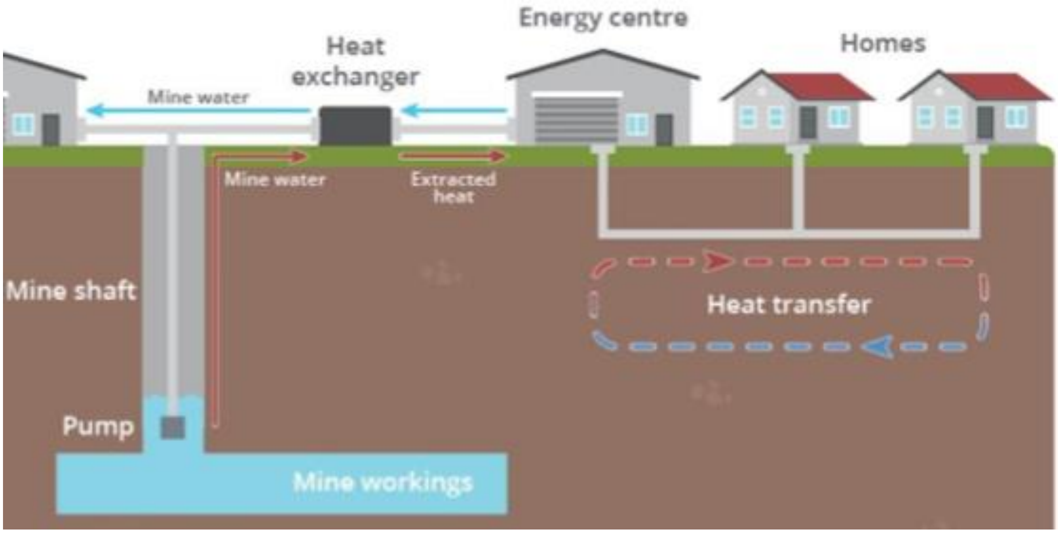


Figure C2: Diagram of a geothermal district heating system (Source: Mining Remediation Authority, X)

Hydrogen Boiler: A hydrogen boiler uses hydrogen gas as a fuel to produce heat for your home. It works in a similar way to a traditional gas boiler, but instead of burning natural gas, it uses hydrogen gas to produce heat. The diagram below shows an illustration of a hydrogen boiler:

Figure C3: Image of a hydrogen boiler (Source: Remeha)

Solar Electric Boiler: A solar electric boiler uses electricity to produce heat for your home. The electricity is generated from solar energy and powers the solar-compatible electric boiler. The diagram below shows how a solar electric boiler system works:

Figure C4: Diagram of house with solar panels and a solar electric boiler (Source: iStock)

Air Source Heat Pump: An air source heat pump extracts heat from the outside air to produce heat for your home. The heat is compressed using refrigerant fluid and transferred to your heating system via a heat exchanger. The diagram below shows how an air source heat pump works:

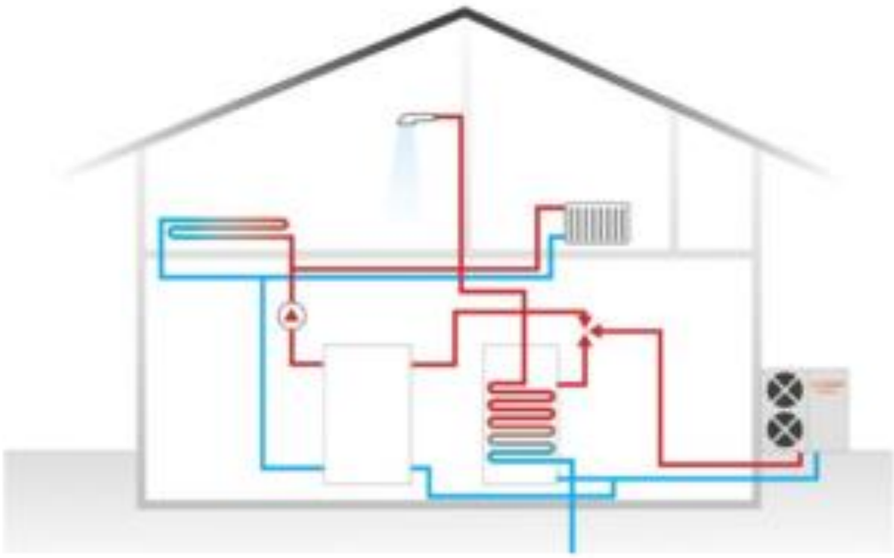


Figure C5: Diagram of a ground source heat pump (Source: WDS Green Energy)

The above heating systems differ in terms of the following attributes:

1. **Investment Cost:** Cost of installation and connection to pipelines/grid of the heating system (in Great British Pounds, £);
2. **Monthly Cost:** Monthly cost of the heating system for usage, maintenance and repair costs, and fuel costs where relevant (in £);
3. **Replacement Period:** The time from installation to dismantling/end-of-life of the heating system (in years).
4. **CO2 Emissions:** The quantity of carbon dioxide (CO2) / equivalent the heating system creates throughout its lifecycle; in production, usage, and disposal (in kilogrammes (kg) per year). For reference, the equivalent CO2emissions for an average gas boiler in the UK is 4700 kgs per year. This is equivalent to 21,000 miles of driving a petrol car, or roughly 74 trips from Newcastle to London.
5. **Job Creation:** The number of jobs (in full-time equivalent jobs) created by the heating system (for example, engineering, construction, plant operators, managers, etc.) when 1000 households adopt the heating system.

Please continue to the next page. The choice cards will appear, each of them containing the heating system options (geothermal district heating, hydrogen boiler, solar electric boiler, and air source heat pump), but with different levels of the attributes (investment cost, monthly cost, replacement period, CO2emissions, and job creation).

Please select your most preferred heating system based on the attributes of each alternative, and please consider each choice card independently. If you are completing this survey on a mobile phone, please rotate the phone to view the full choice card.

Among the following heating options, which one do you prefer?
(Followed by 12 choice cards)

Survey Part 3: Socio-demographic characteristics

Q21: Please input the first half of your postcode (e.g. if postcode DH1 XXX then write 'DH1', if postcode DH11 XXX then write 'DH11')

A21: Free text

Q22: What is your age?

A22: Under 25/ 25-34/ 35-44/ 45-54/ 55-64/ 65 and above

Q23: Which gender do you identify with?
A23: Female / Male / Other / Prefer not to say

Q24: What is your legal marital or registered civil partnership status?
A24: Single / Married / Other / Prefer not to say

Q25: How many people are there in your household?
A25: 1 / 2 / 3 / 4 / 5 and more

Q26: Of which, how many are dependent children?
A26: None / 1 / 2 / 3 or more

Q27: What is your country of birth? [Please input the full country name in text below].
A27: Drop down of all country names

Q28: Which level best describes your educational achievement?
A28: No education / Primary school / Secondary school / Further Education (College/ Technical Qualification) / University degree: Under Graduate / University Degree: Post Graduate / Professional or vocational education / Prefer not to say

Q29: What is your employment status? [Tick all the boxes that apply]
A29: Working as an employee /Self-employment or freelance work/ Unemployed
Retired / Student / Long-term sick or disabled / Looking after home or family / None of above

Q30: What is your full job title? (Such as Retail Assistant, Office Cleaner, District Nurse, Primary School Teacher, Director, or Manager - Do not state your grade or pay band) [Please input in text below).
A30: Free text

Q31: Which option do you think describes your job sector? - Selected Choice/ If other, please specify.
A31: Agriculture / Mining and quarrying / Manufacturing / Electricity, gas, steam, air conditioning supply / Water supply, sewerage, waste management and remediation activities / Construction / Wholesale and retail trade; repair of motor vehicles and motorcycles/ Transport and storage / Accommodation and food service activities / Information and communication / Financial and insurance activities / Real estate activities / Professional, scientific, and technical activities / Administrative and support service activities / Public administration and defence; compulsory social security / Education / Human health and social work activities / Other, please specify:

Q32: What is your total annual household income (before taxes and deducation)?
A32: 0-£15,000 / £15,000-£30,000 / £30,000-£45,000 / £45,000-£60,000 / £60,000-£75,000 / £75,000-£90,000 / £90,000 or more / Prefer not to say

Q33: In total, how many cars or vans are owned or available for use by people in the household?
A33: None / 1 / 2 / 3 and more

Survey Part 4: Housing Characteristics
Q34: Does your household own or rent this accommodation?
A34: I own the accommodation outright / I own the accommodation with a mortgage or loan / I rent (with or without housing benefits) / I live here rent-free

Q35: What type of accommodation is this?
A35: Detached / Semi-detached / Terraced (including end-terrace) / A flat, maisonette or apartment / A mobile or temporary structure: A caravan, mobile home or other mobile or temporary structure / Other: please specify

Q36: How many bedrooms does your accommodation have?
A36: 1 / 2 / 3 / 4 and more

Q37: How long have you been living in this accommodation?
A37: Less than one year / Two to three years / Four to five years / Six to ten years / Ten or more years

Q38: How long do you expect to live in this accommodation in the future?
A38: Less than five years / Six to ten years / Ten or more years

Q39: What type of heating system does this accommodation have? [Tick all the boxes that apply]
A39: No central heating / Gas / Electricity / Oil / Wood burner / Solar electric boiler / Air source heat pump / Other renewable energy source / District or communal heat network / Other (please specify-free text)

Q40: What is the Energy Performance rating of this accommodation? ('A' being the highest energy efficiency, and 'E and below' being the lowest energy efficiency)
A40: A&B / C / D / E and below / I cannot remember or do not know

Q41: What is the council tax band for this accommodation ('E and above' being the highest tax band and 'A' being the lowest tax band)

A41: E and above / D / C / B / A / I cannot remember or do not know

Appendix C2: Choice card attribute levels

Mackenzie *et al.* (forthcoming) detail the calculation of the different heating system attributes for the choice card. An overview from this paper is provided in table C1 below.

Monthly cost and CO2 emissions are based on estimates of average energy use for an average UK house with 2 to 3 bedrooms, 12,000 kWh electricity per year (Ofgem, a).

Table C1: Table detailing sources of attribute level settings

Geothermal District Heating		
Investment Cost	£3,000, £4,000, £5,000, £6,000	Gudmundsson *et al.* (2013): €2500-3900 Denmark, convert using 2013 exchange rate (€1=£0.8492) and inflation-adjust to 2023 prices gives £2849-4444. In line with WTP study in Germany (Krikser *et al*., 2020).
Monthly Cost	£20, £60, £100, £150	Gudmundsson *et al.* (2013): operating and maintenance cost estimated at 2.5% of investment cost per property for the heat network supplier. £1596-3019 per year, £40-75 per month. Beckers and Young (2017): US study 1% of investment cost which ranged from \$3000-\$6000. £2.50-£5 per month.
Replacement Period	16 years, 18 years, 20 years, 25 years	Fasci (2022): 20-25 years for heat pump and exchanger. Bleicher and Gros (2016): 100 years for underground technology.
CO2 emissions	100kg, 250kg, 600kg, 950kg	Usage of energy to power the heat pump technology. Coefficient of performance (COP) 3.5-4 (Banks *et al.,* 2019) used to scale down electricity requirement, 85g CO2e per kWh (Evans, 2020), 291kg CO2e per year. Scale up for production and disposal of system to obtain lifecycle emissions.
Job creation	5, 10,	Based on estimates from other technologies.

	20, 30	
Hydrogen Boiler		
Investment Cost	£1,500, £2,500, £3,500, £4,500	Hart *et al.* (2015): £3500 per household on average. British Gas (2024) and The Engineer (2021): Gas boiler manufactures promote that cost will be in line with natural gas boilers of £1500-4000.
Monthly Cost	£60, £110, £160, £210	Cost of hydrogen gas used, more expensive than natural gas due to energy-intensive nature of hydrogen production. National Infrastructure Commission (2023): UK home £1550-2370 annual, £129-198 monthly. Parkinson *et al.* (2019): significant uncertainty, low \$0.96 per kg hydrogen from coal gasification, high \$14.87-17.30 per kg hydrogen powered by solar energy. Molloy (2019): 1kg hydrogen produces 33kWh electricity.
Replacement Period	12 years, 13.5 years, 15 years, 20 years	Hart *et al*. (2015): micro-combined heat and power (CPH) systems 10-15 years lifespan. Mckay (2023): natural gas boiler average lifetime 10-20 years.
CO_2 emissions	100kg, 1000kg, 5000kg, 11000kg	Depends greatly on source of hydrogen. Lowest 0.31kg CO_2e per kg hydrogen from biomass gasification (Parkinson *et al.,* 2019). Highest 30.9kg CO_2e per kg hydrogen (Molley, 2019)
Job creation	5, 10, 20, 30	Based on estimates from other technologies.
Solar Electric Boiler		
Investment Cost	£8,000, £9,500, £11,000, £12,500	Market price inclusive of installation costs. £6299 for soalr panels, £1000-3500 for electric boiler compatible with solar panels (Ecoexpert, 2024).
Monthly Cost	£80, £120, £160, £200	Mainly composed of maintenance costs for boiler and soalr panels.

		Li *et al.* (2018) £1200-1500 over lifespan, £3-6.25 per month. Cost of servicing, cleaning, assumed replacement of one solar panel and the inverter over possible 30-year lifetime, monthly cost of £52-68. Intermittency in solar energy in UK, account for electricity costs from national grid during peak winter £112-188. (Howell 2023; Ideal Heat Solutions, 2023).
Replacement Period	20 years, 22.5 years, 25 years, 30 years	Odeh *et al*. (2013): solar panels last 30 years Scholfield (2024): solar electric boilers last 15-25 years.
CO2 emissions	100kg, 650kg, 1200kg, 1800kg	Primarily stem from production and disposal of heating system rather than usage. Including extraction of raw materials. Parliamentary Office of Science and Technology (2016): 10g CO2e per kWh Department for Energy and Climate Change (2014): 149g CO2e per kWh.
Job creation	5, 10, 20, 30	Fernandez (2024) and Lempriere (2024): similar to air source heat pumps 0.3 full time equivalent (FTE) jobs per installation. Scale up to 1000 installations, 30 FTE. Lower bound set to 5 FTE, consistent with other DCE studies on job creation as a heating system attribute (Maxim and Roman, 2019; Maxim *et al.,* 2022).
Air Source Heat Pump		
Investment Cost	£6,000, £7,500, £9,000, £10,500	Energy Saving Trust, (2024b): £5000-15,000
Monthly Cost	£90, £110, £130, £150	COP of 2.8 2020-2023 (Harris and Walker, 2023), seasonable performance factor (SPF) averaged over the year is 2.5, used to scale down household electricity requirement. Electricity price at Energy Price Cap of 28.62 pence per kWh, monthly cost £114 (Ofgem, b). Annual servicing £100-300 (Crossley, 2023).

Replacement Period	16 years, 18 years, 20 years, 25 years	BEIS (2021a), Lin *et al.* (2021): 20 years.
CO_2 emissions	350kg, 1150kg, 2000kg, 3000kg	COP 2.5-3 (Chesser *et al*. 2021; Harris and Walker, 2023), used to scale down electricity requirement. 288-816kg CO_2 per year based on low carbon electricity sources (Parliamentary Office of Science and Technology, 2016). Clarke (2019): 1600kg per year ISO Energy (2023): 2453 kg per year
Job creation	5, 10, 20, 30	Heptonstall and Winskel (2023): 0.3 FTE per installation.

<u>Appendix C3: ArcGIS maps of Coal Mine Locations</u>

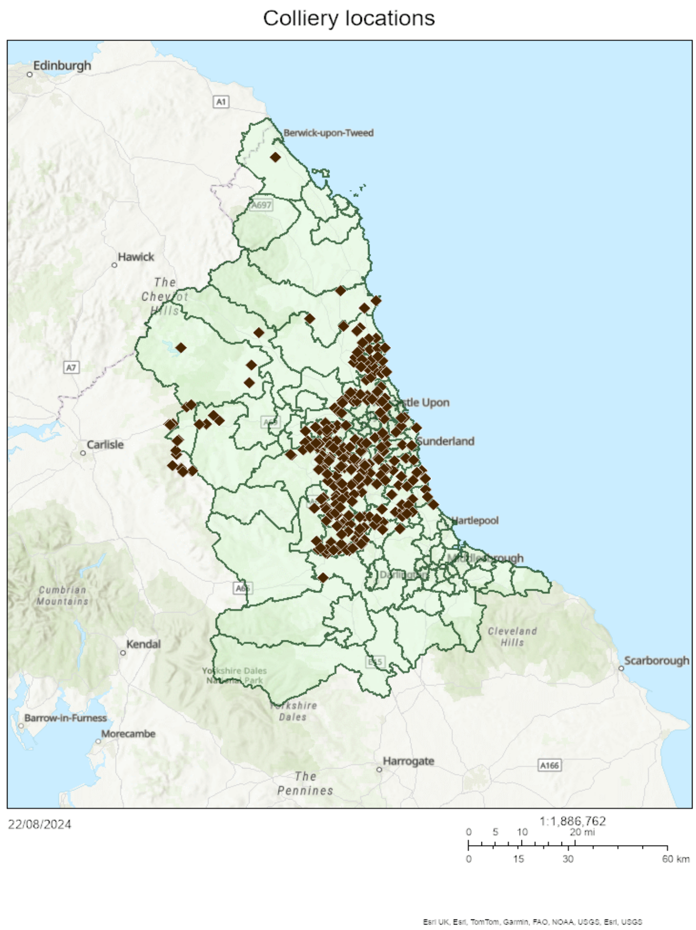


Figure C6: ArcGIS map showing mine locations and postcode areas

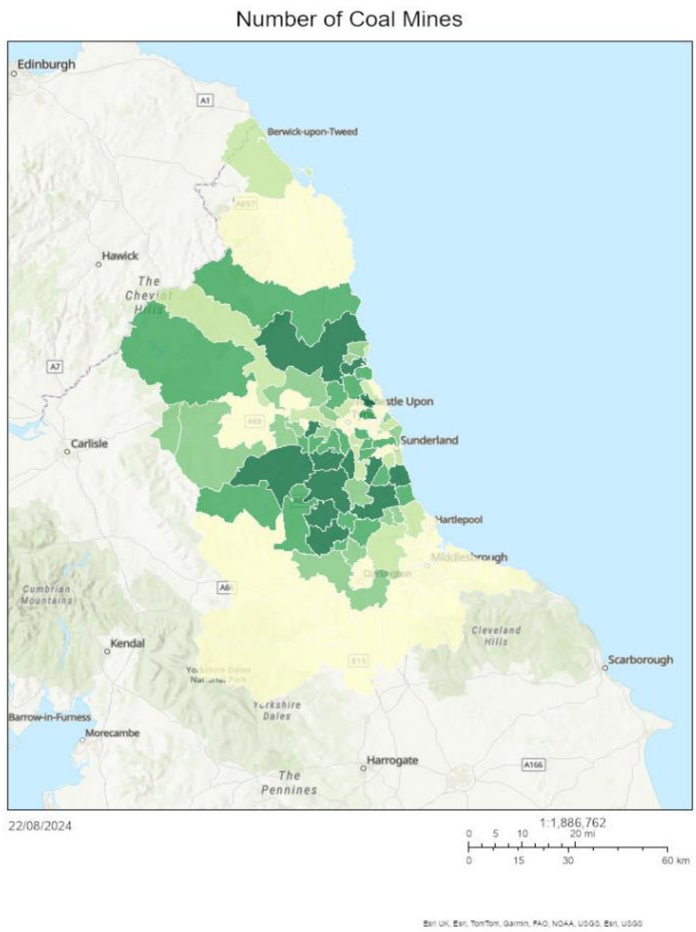


Figure C7: ArcGIS map showing density of coal mines in postcode areas

Appendix C4: Mixed logit parameter distribution checks

We ran the mixed logit model with alternative distributions for the CO2 emissions coefficient and the job creation coefficient.

First, we estimated a normal distribution with a restricted standard deviation (Theine and Scarpa, 2009). In model D1, we fix the mean of the coefficient on CO2 emissions at the value calculated in the mixed logit model 2. We then calculate what the standard deviation must be for only 5% of the distribution to fall above zero.

$$z = \frac{x - \mu}{\sigma} \rightarrow 1.64 = \frac{0 + 2.542}{\sigma}$$

$$\sigma = \frac{2.542}{1.64} = 1.55 \quad (C4.1)$$

In model D3, we restrict the standard deviation of the normal distribution of the job creation coefficient in a similar way.

$$-1.64 = \frac{0 - 0.9376}{\sigma}$$

$$\sigma = \frac{0.9376}{1.64} = 0.571. \qquad (C4.2)$$

In model D2 and D4 we assume that the random coefficients for the CO2 and job creation attributes follow a truncated normal distribution, where the CO2 coefficient is truncated $[-\infty, 0]$ and the job creation attribute is truncated $[0, \infty]$. Within apollo we take draws, p, from the uniform distribution and transform these draws into draws from the truncated normal by the inverse normal cumulative distribution function.

$$x = \Phi^{-1}\left(\Phi(a;\bar{\mu},\bar{\sigma}) + p * \left(\Phi(b;\bar{\mu},\bar{\sigma}) - \Phi(a;\bar{\mu},\bar{\sigma})\right);\bar{\mu},\bar{\sigma}\right)$$

where a is lower bound and b is the upper bound of the truncation, $\bar{\mu}$ and $\bar{\sigma}$ are the mean and standard deviation of the 'parent' general normal probability distribution function, and Φ is the cumulative normal distribution function, and Φ^{-1} the inverse of this.

Model 2 is the mixed logit model with starting values of zero for the parameter estimates. To facilitate a precise comparison of the restricted model with the unrestricted model, Model 2a and 2b have starting values which match the restriction placed in model C1 and C3 respectively, but do not restrict the value of these parameters in the estimation. This step was taken due to the fact that model C3 outperformed model 2 despite having a lower degree of freedom.

Table C2: Estimation of Mixed Logit models to test Normal (Model 2) vs Truncated Normal Distribution Assumptions (Models C1 and C3)

	MXL Model 2	MXL Model 2a	MXL Model 2b	MXL restricted normal CO2 Model C1	MXL restricted normal job Model C3
ASC_{geo}	0.125 (1.47)	0.124 (1.45)	0.121 (1.43)	0.168 (2.00)**	0.120 (1.44)
ASC_{hyd}	-0.410	-0.410	-0.412	-0.188	-0.407

	(3.63)***	(3.62)	(3.65)	(1.76)*	(3.63)***
ASC_{sol}	0.712 (7.86)***	0.711 (7.85)	0.711 (7.86)	0.691 (7.75)***	0.705 (7.87)***
ASC_{pum}	0.000 (fixed)	0.000 (fixed)	0.000 (fixed)	0.000 (fixed)	0.000 (fixed)
$\beta_{InvCost}$	0.671 (11.68)*** {4.642}[1]	0.682 (11.98) {4.733}	0.671 (11.67) {4.572}	0.630 (11.34)*** {4.411}[1]	0.679 (12.25)*** {4.839}[1]
$\sigma_{InvCost}$	1.315 (33.50)*** {9.995}[1]	1.321 (34.98) {10.289}	1.303 (30.87) {9.657}	1.307 (33.13)*** {9.377}[1]	1.34 (-27.45)*** {10.845}[1]
$\beta_{MonCost}$	-0.286 (-3.59)*** {2.786}[1]	-0.287 (-3.63) {2.712}	-0.263 (-3.26) {2.787}	-0.300 (-3.86)*** {2.501}[1]	-0.293 (-3.72)*** {2.632}[1]
$\sigma_{MonCost}$	1.619 (20.62)*** {9.948}[1]	1.603 (28.64) {9.419}	1.605 (29.33) {9.713}	1.560 (25.55)*** {8.065}[1]	1.588 (-21.29)*** {8.906}[1]
β_{RepPer}	0.367 (8.62)***	0.367 (8.56)	0.363 (8.49)	0.337 (8.11)***	0.365 (8.63)***
σ_{RepPer}	0.875 (14.45)***	-0.860 (13.34)	0.866 (14.13)	0.963 (15.77)***	0.869 (13.96)***
β_{CO2}	-2.542 (12.83)***	-2.557 (12.70)	-2.544 (12.89)	-2.54 (fixed)	-2.549 (12.62)***
σ_{CO2}	3.724 (16.19)***	3.720 (16.01)	-3.779 (16.28)	1.55 (fixed)	-3.708 (16.86)***
β_{Job}	0.937 (5.83)***	0.944 (5.95)	0.946 (5.87)	0.879 (5.71)***	0.937 (fixed)
σ_{Job}	1.460 (3.21)***	1.577 (3.84)	1.433 (2.93)	-1.342 (3.05)***	0.571 (fixed)
LL	-10489.41	-10486.94	-10486.55	-10659.02	-10487.84
LRT p-value				1.866 e-07 Reject model D1	0.273 Cannot reject model D3

*Absolute values of z-statistics in brackets, * 90% confidence, ** 95% confidence, *** 99% confidence correspond with 2-sided critical values 1.64, 1.96, 2.58 respectively.* *Where heating alternatives {geo, hyd, sol, pum} represent geothermal district heating, hydrogen boiler, solar electric boiler, and air source heat pump respectively.*

Table C3: Estimation of Mixed Logit models to test Normal (Model 2) vs Log-Normal Distribution Assumptions (Models C2, C4 and C5)

	MXL Model 2	MXL lognormal CO2 Model C2	MXL lognormal job Model C4	MXL lognormal job co2 and job Model C5
ASC_{geo}	0.125 (1.47)	0.175 (2.02)	0.130 (1.52)	0.179 (2.04)
ASC_{hyd}	-0.410 (3.63)***	-0.388 (3.49)	-0.403 (3.53)***	-0.379 (-3.36)
ASC_{sol}	0.712 (7.86)***	0.717 (7.74)	0.716 (7.85)***	0.720 (7.67)
ASC_{pum}	0.000 (fixed)	0.000 (fixed)	0.000 (fixed)	0.000 (fixed)
$\beta_{InvCost}$	0.671 (11.68)*** {4.642}[1]	0.636 (10.99) {4.630}[1]	0.662 (11.44)*** {4.603}	0.654 (11.17)
$\sigma_{InvCost}$	1.315 (33.50)*** {9.995}[1]	1.339 (-27.37) {10.359}[1]	1.315 (34.05)*** {9.910}	1.362 (38.87)
$\beta_{MonCost}$	-0.286 (-3.59)*** {2.786}[1]	-0.521 (-5.64) {2.985}[1]	-0.282 (-3.56)*** {2.806}	-0.498 (5.31)
$\sigma_{MonCost}$	1.619 (20.62)*** {9.948}[1]	1.797 (23.47) {14.702}[1]	1.621 (22.17)*** {10.056}	1.763 (30.35)
β_{RepPer}	0.367 (8.62)***	0.257 (5.91)	0.370 (8.62)***	0.270 (6.14)
σ_{RepPer}	0.875 (14.45)***	1.067 (16.68)	0.870 (14.58)***	1.050 (16.33)

β_{CO2}	-2.542 (12.83)***	-0.639 (4.51) {}	-2.582 (12.81)***	-0.676 (-3.47)
σ_{CO2}	3.724 (16.19)***	2.996 (31.05) {}	-3.78 (16.01)***	2.955 (23.53)
β_{Job}	0.937 (5.83)***	0.616 (3.86)	-1.259 (3.76)*** {}	-2.800 (-3.64)
σ_{Job}	1.460 (3.21)***	1.403 (3.23)	1.578 (11.39)*** {}	2.386 (7.46)
LL	-10489.41	-10377.73	-10471.34	-10364.17
LRT p-value				
BAS p-value		3.192e-51 Reject model 2	7.51 e-10 Reject model 2	3.387e-57 Reject model 2

*Absolute values of z-statistics in brackets, * 90% confidence, ** 95% confidence, *** 99% confidence correspond with 2-sided critical values 1.64, 1.96, 2.58 respectively.*

Where heating alternatives {geo, hyd, sol, pum} represent geothermal district heating, hydrogen boiler, solar electric boiler, and air source heat pump respectively.

[1]*Moments of the log-normal estimations in curly brackets, where* $\mu_\beta = -\exp\left(\mu_{log\,\beta} + \frac{\sigma^2_{log\,\beta}}{2}\right)$, *and*

$$\sigma_\beta = \mu_\beta * \sqrt{\exp\left(\sigma^2_{\log\beta}\right) - 1}$$

Comparing models 2a and model C1 in table C2 shows that restricting the standard deviation of the CO2 parameter leads to a significantly worse fit. However, comparing models 2b and C2 demonstrates that restricting the standard deviation of the job creation parameter does not significantly worsen the fit of the model. Henceforth, we would not reject the restricted model with the favourable behavioural interpretation that only 5% of the sample have negative preferences for job creation.

Appendix C5: ICLV MXL with correlation

Table C4.1: Estimation of Measurement Equation of Environmental Attitude Latent Variable Model within Model 5a, 5b, and 5c.

Environmental Attitude			
	ICLV Env Ene MNL (Model 5a)	**ICLV Env Ene** MXL (Model 5b)	**ICLV Env Ene** MXL cor (Model 5c)
η^{concEnv}	-0.422 (3.86)***	-0.402 (3.88)***	-0.324(2.70)***
τ_1^{concEnv}	-3.865 (16.55)***	-4.064 (17.00)***	-3.965(16.94)***
τ_2^{concEnv}	-2.782 (18.51)***	-2.984 (18.34)***	-2.888(18.36)***
τ_3^{concEnv}	-1.526 (14.05)***	-1.738 (14.19)***	-1.649(14.65)***
τ_4^{concEnv}	0.719 (7.32)***	0.497 (5.09)***	0.559(6.39)***
$\eta^{\text{changeLife}}$	-0.309 (3.11)***	-0.457 (4.40)***	-0.352(2.70)***
$\tau_1^{\text{changeLife}}$	-3.932 (16.19)***	-4.217 (16.86)***	-4.090(16.46)***
$\tau_2^{\text{changeLife}}$	-2.871 (18.73)***	-3.148 (18.38)***	-3.025(18.32)***
$\tau_3^{\text{changeLife}}$	-1.698 (16.27)***	-1.959 (14.94)***	-1.845(15.30)***
$\tau_4^{\text{changeLife}}$	0.916 (10.60)***	0.712 (6.95)***	0.781(8.43)***
$\eta^{\text{shouldChange}}$	-0.430 (4.01)***	-0.474 (4.37)***	-0.374(2.95)***
$\tau_1^{\text{shouldChange}}$	-4.036 (15.87)***	-4.3 (15.86)***	-4.169(15.77)***
$\tau_2^{\text{shouldChange}}$	-3.23 (18.06)***	-3.492 (17.53)***	-3.365(17.69)***
$\tau_3^{\text{shouldChange}}$	-1.753 (15.04)***	-2.011 (14.85)***	-1.895(15.31)***
$\tau_4^{\text{shouldChange}}$	0.652 (6.80)***	0.409 (3.99)***	0.485(5.24)***
*With absolute values of robust z-statistics in brackets, * 90% confidence, ** 95% confidence, *** 99% confidence correspond with 2-sided critical values 1.64, 1.96, 2.58 respectively. Bolduc et al. (2005) normalisation applied.*			

Table C4.2: Estimation of Measurement Equation of Energy Attitude Latent Variable Model within Model 5a, 5b, and 5c.

Energy Attitude			
	ICLV Env Ene MNL (Model 5a)	**ICLV Env Ene** MXL (Model 5b)	**ICLV Env Ene** MXL cor (Model 5c)
$\eta^{\text{adjThermKnow}}$	0.384 (4.29)***	2.226 (10.00)***	2.118(6.68)***
$\tau_1^{\text{adjThermKnow}}$	-3.365 (18.28)***	-5.176 (10.59)***	-5.315(9.38)***
$\tau_2^{\text{adjThermKnow}}$	-2.566 (18.42)***	-4.058 (9.08)***	-4.243(8.54)***
$\tau_3^{\text{adjThermKnow}}$	-2.009 (17.14)***	-3.254 (7.58)***	-3.463(7.64)***
$\tau_4^{\text{adjThermKnow}}$	0.133 (1.48)	0.296 (0.74)	-0.025(0.07)
$\eta^{\text{adjThermHave}}$	0.308 (3.49)***	1.609 (10.52)***	1.543(7.48)***
$\tau_1^{\text{adjThermHave}}$	-3.742 (17.21)***	-4.861 (12.15)***	-4.983(12.12)***

$\tau_2^{\text{adjThermHave}}$	-2.454 (18.87)***	-3.305 (10.27)***	-3.469(10.54)***
$\tau_3^{\text{adjThermHave}}$	-1.642 (15.91)***	-2.273 (7.35)***	-2.458(8.26)***
$\tau_4^{\text{adjThermHave}}$	0.551 (6.67)***	0.861 (2.92)***	0.612(2.38)**
$\eta^{\text{redEnergy}}$	0.472 (4.83)***	3.019 (7.50)***	2.763(4.52)***
$\tau_1^{\text{redEnergy}}$	-4.262 (15.86)***	-7.746 (8.32)***	-7.588(6.24)***
$\tau_2^{\text{redEnergy}}$	-3.074 (18.25)***	-5.759 (7.67)***	-5.785(5.99)***
$\tau_3^{\text{redEnergy}}$	-2.306 (17.14)***	-4.459 (6.58)***	-4.578(5.58)***
$\tau_4^{\text{redEnergy}}$	0.216 (2.21)**	0.588 (1.09)	0.142(0.32)
η^{energyDM}	0.594 (6.41)***	1.691 (11.52)***	1.736(10.31)***
τ_1^{energyDM}	-4.649 (15.01)***	-5.75 (12.56)***	-6.050(13.17)***
τ_2^{energyDM}	-3.294 (18.14)***	-4.14 (11.24)***	-4.452(11.97)***
τ_3^{energyDM}	-2.119 (15.31)***	-2.699 (7.92)***	-2.999(8.97)***
τ_4^{energyDM}	-0.124 (1.11)	-0.019 (0.06)	-0.281(0.97)
*With absolute values of robust z-statistics in brackets, * 90% confidence, ** 95% confidence, *** 99% confidence correspond with 2-sided critical values 1.64, 1.96, 2.58 respectively. Bolduc et al. (2005) normalisation applied.*			

Table C4.3: Estimation of Structural Equation of Environmental Attitude Latent Variable Model within Model 5a, 5b, and 5c.

Environmental Attitude			
	ICLV Env Ene (All) (Model 5: MNL)	**ICLV Env Ene** (All) (Model 5: MXL)	**ICLV Env Ene** (All) (Model 5: MXL corr)
γ_{LowInc}	-0.144 (1.86)*	0.143 (2.07)**	0.070 (0.87)
γ_{Male}	-0.004 (0.05)	0.048 (0.69)	0.091 (1.00)
γ_{UniEduc}	-0.102 (1.29)	-0.132 (1.78)*	-0.111 (1.23)
γ_{Unemp}	-0.005 (0.03)	0.266 (1.51)	0.067 (0.27)
$\gamma_{\text{Age 35}}$	-0.068 (0.56)	0.44 (3.50)***	0.336 (2.35)**
γ_{Age3555}	0.058 (0.51)	0.396 (3.58)***	0.335 (2.61)***
γ_{OwnAccom}	0.109 (1.19)	0.14 (1.32)	0.158 (1.58)
γ_{Renew}	-0.079 (0.53)	0.38 (2.22)**	0.284 (1.98)**
γ_{Time10}	0.057 (0.61)	0.021 (0.25)	-0.079 (0.70)
$\gamma_{\text{ExpTime10}}$	-0.012 (0.13)	0.029 (0.36)	-0.055 (0.56)
*With absolute values of robust z-statistics in brackets, * 90% confidence, ** 95% confidence, *** 99% confidence correspond with 2-sided critical values 1.64, 1.96, 2.58 respectively.*			

Table C4.4: Estimation of Structural Equation of Energy Attitude Latent Variable Model within Model 5a, 5b, and 5c.

Energy Attitude			
	ICLV Env Ene (All) (Model 5: MNL)	**ICLV Env Ene** (All) (Model 5: MXL)	**ICLV Env Ene** (All) (Model 5: MXL corr)
γ_{LowInc}	-0.140 (1.80)*	-0.218 (2.54)**	-0.224 (2.39)**
γ_{Male}	-0.041 (0.54)	0.143 (1.73)*	0.124 (1.54)
γ_{UniEduc}	0.092 (1.22)	0.12 (1.29)	0.073 (0.85)
γ_{Unemp}	-0.214 (1.38)	-0.328 (1.57)	-0.226 (1.34)
$\gamma_{\text{Age 35}}$	-0.522 (3.96)***	-0.51 (3.52)***	-0.644 (4.76)***
γ_{Age3555}	-0.306 (2.74)***	-0.199 (1.56)	-0.258 (2.14)**
γ_{OwnAccom}	0.026 (0.27)	0.235 (2.39)**	0.163 (1.77)*
γ_{Renew}	-0.527 (4.28)***	-0.336 (1.98)**	-0.341 (2.11)**
γ_{Time10}	0.187 (2.11)**	0.013 (0.13)	-0.018 (0.18)
$\gamma_{\text{ExpTime10}}$	0.081 (0.95)	0.316 (3.30)***	0.283 (3.14)***
*With absolute values of robust z-statistics in brackets, * 90% confidence, ** 95% confidence, *** 99% confidence correspond with 2-sided critical values 1.64, 1.96, 2.58 respectively.*			

Table C4.5: Estimation of Structural Equation Choice Model within Model 5a, 5b, and 5c.

	ICLV Env Ene MNL (Model 5a)	s.e.	**ICLV Env Ene MXL** (Model 5b)	s.e	**ICLV Env Ene MXL cor** (Model 5c)	s.e
ASC_{geo}	1.575 (5.13)***	0.307	0.799 (3.76)***	0.212	0.762 (3.25)***	0.234
ASC_{hyd}	1.507 (4.15)***	0.363	-0.053 (0.19)	0.274	0.198 (0.69)	0.286
ASC_{sol}	0.769 (2.86)***	0.269	-0.366 (1.57)	0.233	-0.168 (0.64)	0.263
ASC_{pum}	0.000(fixed)	(fixed)	0.000 (fixed)	(fixed)	0.000 (fixed)	(fixed)
β_{invCost}	-2.3 (10.05)***	0.229	0.869 (5.74)*** {-4.150}[1]	0.151	0.737 (4.90)*** {-3.495}[1]	0.15
σ_{invCost}			1.053 (13.1)*** {1.238}[1]	0.08	-1.014 (6.86)*** {0.988}[1]	0.148
β_{monCost}	-1.558 (10.08)***	0.155	0.319 (3.28)*** {-2.402}[1]	0.097	0.263 (2.38)** {-2.426}[1]	0.11
σ_{monCost}			1.056 (14.15)*** {0.456}[1]	0.075	1.116 (8.34)*** {0.414}[1]	0.134
β_{repPer}	0.573 (7.78)***	0.074	0.689 (7.64)***	0.09	0.7 (7.42)***	0.094
σ_{repPer}			0.651 (8.70)***	0.075	0.613 (6.82)***	0.09
β_{co2}	-1.864 (7.87)***	0.237	-3.084 (8.64)***	0.357	-2.969 (9.25)***	0.321
σ_{co2}			2.509 (9.48)***	0.265	2.297 (9.26)***	0.248
β_{job}	1.688 (6.47)***	0.261	2.128 (6.97)***	0.305	1.925 (6.70)***	0.287
σ_{job}			2.481 (6.77)***	0.366	-2.285 (6.13)***	0.373

$\beta_{\text{inv,co2}}^{\text{cov}}$					0.577 (7.05)***	0.082
$\lambda_{\text{geo}}^{\text{env}}$	0.643 (2.52)**	0.255	-1.394 (6.52)***	0.214	-1.314 (5.67)***	0.232
$\lambda_{\text{hyd}}^{\text{env}}$	1.731 (8.37)***	0.207	0.414 (1.41)	0.294	0.456 (1.58)	0.289
$\lambda_{\text{sol}}^{\text{env}}$	1.338 (6.81)***	0.197	1.145 (6.11)***	0.188	1.186 (5.96)***	0.199
$\lambda_{\text{invCost}}^{\text{env}}$	-0.39 (2.21)**	0.176	1.531 (7.66)***	0.2	1.398 (7.04)***	0.199
$\lambda_{\text{monCost}}^{\text{env}}$	0.591 (5.42)***	0.109	0.546 (7.58)***	0.072	0.503 (5.84)***	0.086
$\lambda_{\text{repPer}}^{\text{env}}$	-0.188 (3.03)***	0.062	-0.348 (4.63)***	0.075	-0.31 (4.03)***	0.077
$\lambda_{\text{co2}}^{\text{env}}$	1.096 (7.08)***	0.155	1.373 (7.63)***	0.18	1.197 (7.39)***	0.162
$\lambda_{\text{job}}^{\text{env}}$	-0.949 (3.90)***	0.243	-1.209 (4.72)***	0.256	-1.046 (3.77)***	0.278
$\lambda_{\text{geo}}^{\text{ene}}$	1.696 (9.81)***	0.173	0.211 (1.11)	0.19	0.472 (1.63)	0.29
$\lambda_{\text{hyd}}^{\text{ene}}$	1.394 (7.54)***	0.185	0.879 (3.68)***	0.239	0.974 (2.81)***	0.346
$\lambda_{\text{sol}}^{\text{ene}}$	-0.225 (1.33)	0.169	0.442 (2.30)**	0.192	0.425 (1.42)	0.3
$\lambda_{\text{invCost}}^{\text{ene}}$	-0.777 (10.38)***	0.075	-0.182 (3.15)***	0.058	-0.322 (3.93)***	0.082
$\lambda_{\text{monCost}}^{\text{ene}}$	-1.204 (9.19)***	0.131	0.355 (2.10)**	0.169	0.006 (0.03)	0.195
$\lambda_{\text{repPer}}^{\text{ene}}$	0.274 (4.98)***	0.055	0.136 (2.38)**	0.057	0.195 (2.66)***	0.073
$\lambda_{\text{co2}}^{\text{ene}}$	-0.852 (7.13)***	0.119	-0.504 (3.53)***	0.143	-0.705 (3.84)***	0.184
$\lambda_{\text{job}}^{\text{ene}}$	0.565 (2.82)***	0.200	-0.114 (0.57)	0.199	0.157 (0.71)	0.222
LL (choice model only)	-9564.05		-9,251.21		-9183.79	

*Absolute values of robust z-statistics in brackets, * 90% confidence, ** 95% confidence, *** 99% confidence correspond with 2-sided critical values 1.64, 1.96, 2.58 respectively.*

[1]*Moments of the log-normal estimations in curly brackets, where*

$$\mu_\beta = -\exp\left(\mu_{log\,\beta} + \frac{\sigma_{log\,\beta}^2}{2}\right), \text{ and } \sigma_\beta = \mu_\beta * \sqrt{\exp\left(\sigma_{\log\beta}^2\right) - 1}$$

Table C4.6: Estimation of Measurement Equation of Identity Latent Variable Model within Model 6a, 6b, and 6c.

Coal Mining Identity			
	ICLV MNL (Model 6a)	ICLV MXL (Model 6b)	ICLV MXL cov (Model 6c)
$\eta^{\text{idenHerit}}$	-0.096 (1.34)	0.021 (0.27)	0.022 (0.28)
$\tau_1^{\text{idenHerit}}$	-2.492 (19.57)***	-2.516 (19.24)***	-2.517 (19.24)***
$\tau_2^{\text{idenHerit}}$	-1.226 (15.05)***	-1.252 (14.28)***	-1.253 (14.27)***
$\tau_3^{\text{idenHerit}}$	0.043 (0.62)	0.014 (0.19)	0.014 (0.18)
$\tau_4^{\text{idenHerit}}$	1.435 (16.49)***	1.404 (15.49)***	1.404 (15.47)***
η^{honHist}	0.235 (3.11)***	0.328 (3.90)***	0.329 (3.91)***
τ_1^{honHist}	-4.164 (15.98)***	-4.297 (16.26)***	-4.298 (16.27)***
τ_2^{honHist}	-2.777 (19.67)***	-2.908 (18.93)***	-2.909 (18.98)***

τ_3^{honHist}	-0.51 (6.58)***	-0.625 (6.84)***	-0.626 (6.89)***
τ_4^{honHist}	1.451 (15.79)***	1.357 (13.86)***	1.356 (13.93)***
η^{projImp}	0.28 (3.84)***	0.367 (4.44)***	0.367 (4.44)***
τ_1^{projImp}	-4.33 (15.43)***	-4.477 (15.66)***	-4.478 (15.68)***
τ_2^{projImp}	-3.507 (18.28)***	-3.654 (18.12)***	-3.654 (18.18)***
τ_3^{projImp}	-1.463 (15.63)***	-1.599 (14.91)***	-1.599 (15.01)***
τ_4^{projImp}	0.649 (7.98)***	0.539 (6.00)***	0.539 (6.04)***
*With absolute z-value in brackets, * 5% sig, ** 2.5% sig. *** 1% sig.* *Bolduc et al. (2005) normalisation applied.*			

Table C4.7: Estimation of Structural Equation of Identity Latent Variable Model within Model 6a, 6b, and 6c

Coal mining identity			
	Hybrid MNL	Hybrid MXL	Hybrid MXL with Cov
γ_{LowInc}	0.003 (0.04)	-0.044 (0.55)	-0.035 (0.45)
γ_{Male}	-0.060 (0.83)	-0.122 (1.61)	-0.125 (1.65)*
γ_{UniEd}	0.091 (1.25)	0.077 (0.96)	0.083 (1.03)
γ_{Unemp}	-0.132 (0.86)	-0.081 (0.46)	-0.074 (0.45)
γ_{Age35}	-0.393 (3.11)***	-0.398 (3.07)***	-0.404 (3.19)***
γ_{Age3555}	-0.261 (2.44)**	-0.388 (3.41)***	-0.389 (3.49)***
γ_{OwnAccom}	-0.092 (1.01)	-0.165 (1.52)	-0.158 (1.47)
γ_{Time10}	0.161 (1.91)*	0.03 (0.33)	0.024 (0.26)
$\gamma_{\text{ExpTime10}}$	0.056 (0.68)	-0.056 (0.62)	-0.058 (0.66)
γ_{NoMines}	-0.002 (0.85)	-0.003 (1.41)	-0.004 (1.47)
*Absolute values of robust z-statistics in brackets, * 90% confidence, ** 95% confidence, *** 99% confidence correspond with 2-sided critical values 1.64, 1.96, 2.58 respectively.*			

Table C4.8: Estimation of Structural Equation of Choice Model within Model 6a, 6b, and 6c

	MNL (Model 1)	**ICLV iden** (Model 6a: MNL)	**ICLV** (Model 6b: MXL)	**ICLV Env Ene** (All) (Model 6c: MXL corr)
ASC_{geo}	0.892 (12.32)***	0.894 (3.69)***	0.743 (3.64)***	0.741 (3.69)***
ASC_{hyd}	0.802 (9.40)***	0.967 (7.60)***	-0.104 (0.41)	-0.108 (0.43)
ASC_{sol}	0.717 (9.13)***	0.064 (0.51)	-0.429 (1.83)*	-0.431 (1.87)*
ASC_{pum}	0.000 (fixed)	0.000 (fixed)	0.000 (fixed)	0.000 (fixed)
β_{invCost}	-0.956 (11.63)***	-1.744 (10.29)***	0.81 (5.50)*** {-4.219}[1]	0.815 (5.79)*** {-4.191}[1]
σ_{invCost}			-1.122 (12.84)*** {1.286}[1]	-1.112 (13.35)*** {1.274}[1]

β_{monCost}	-0.758 (22.03)***	-1.288 (10.22)***	0.278 (2.99)*** {-2.403}[1]	0.277 (3.02)*** {-2.409}[1]
σ_{monCost}			1.095 (12.55)*** {0.422}[1]	1.097 (12.67)*** {0.423}[1]
β_{dur}	0.323 (12.14)***	0.481 (8.00)***	0.653 (8.37)***	0.651 (8.40)***
σ_{dur}			0.64 (8.01)***	0.635 (7.82)***
β_{co2}	-0.775 (12.14)***	-1.437 (7.99)***	-3.009 (9.95)***	-3.009 (10.07)***
σ_{co2}			2.497 (10.65)***	2.496 (10.73)***
β_{job}	0.689 (5.68)***	1.628 (7.43)***	1.952 (6.78)***	1.961 (6.80)***
σ_{job}			-2.371 (6.91)***	-2.373 (7.00)***
$\beta^{\text{cov}}_{\text{inv,job}}$				-0.058 (1.09)
$\lambda^{\text{iden}}_{\text{geo}}$		1.614 (10.98)***	1.501 (7.38)***	1.499 (7.47)***
$\lambda^{\text{iden}}_{\text{hyd}}$		0.622 (4.24)***	-0.2 (0.66)	-0.203 (0.68)
$\lambda^{\text{iden}}_{\text{sol}}$		-0.656 (4.80)***	-1.039 (5.40)***	-1.042 (5.39)***
$\lambda^{\text{iden}}_{\text{invCost}}$		-0.903 (7.47)***	-1.396 (6.91)***	-1.405 (6.88)***
$\lambda^{\text{iden}}_{\text{monCost}}$		-0.795 (17.13)***	-0.579 (8.53)***	-0.577 (8.56)***
$\lambda^{\text{iden}}_{\text{dur}}$		0.263 (5.46)***	0.35 (4.91)***	0.346 (4.81)***
$\lambda^{\text{iden}}_{\text{co2}}$		-1.027 (12.85)***	-1.25 (8.62)***	-1.247 (8.50)***
$\lambda^{\text{iden}}_{\text{job}}$		0.791 (4.35)***	1.008 (4.19)***	1.018 (4.22)***
LL (choice model only)	-12,611.23	-10,512,08	-9,418.16	-9,417.90

*Absolute values of robust z-statistics in brackets, * 90% confidence, ** 95% confidence, *** 99% confidence correspond with 2-sided critical values 1.64, 1.96, 2.58 respectively.*

[1]*Moments of the log-normal estimations in curly brackets, where*

$$\mu_\beta = -\exp\left(\mu_{log\,\beta} + \frac{\sigma^2_{log\,\beta}}{2}\right), \textit{ and } \sigma_\beta = \mu_\beta * \sqrt{\exp\left(\sigma^2_{\log\beta}\right) - 1}$$

Appendix C6: Predictions and regressions

OLS regressions of change in probability of selecting geothermal district heating against different attitudinal latent variables when a carbon tax is imposed.

When a carbon tax is imposed on the investment cost,

$$\text{DifProbGeo}_\text{i} = 0.0434 + 0.00181\ (2.12)\text{EnvAttitude}_{0,\text{i}} \qquad (C5.1)$$

$$\text{DifProbGeo}_\text{i} = 0.0430 + 0.00242\ (3.07)\text{EnvAttitude}_{1,\text{i}} \qquad (C5.2)$$

$$\mathrm{DifProbGeo_i} = 0.0440 + 0.00230\ (2.91)\mathrm{EneAttitude}_{0,\mathrm{i}} \qquad (C5.3)$$

$$\mathrm{DifProbGeo_i} = 0.0441 + 0.00172\ (2.06)\mathrm{EneAttitude}_{1,\mathrm{i}} \qquad (C5.4)$$

Where $\mathrm{DifProbGeo_i}$ is the difference in the probability of a participant choosing geothermal district heating in the base model and the caron price prediction, $\mathrm{EnvAttitude}_{0,\mathrm{i}}$ and $\mathrm{EnvAttitude}_{1,\mathrm{i}}$ are the conditional environmental attitude in the base model and carbon price model respectively, and $\mathrm{EneAttitude}_{0,\mathrm{i}}$ and $\mathrm{EneAttitude}_{1,\mathrm{i}}$ is the conditional energy-saving attitudes for each model. The t-value for the coefficient is reported in brackets. All relations are significant with 95% confidence.

Repeating this for model X, we find that identity is not significantly related to the change in probability of selecting geothermal district heating.

$$\mathrm{DifProbGeo_i} = 0.0322 + 0.000154\ (0.21)\mathrm{Identity}_{0,\mathrm{i}} \qquad (C5.5)$$

$$\mathrm{DifProbGeo_i} = 0.0321 - 0.000293\ (-0.37)\mathrm{Identity}_{1,\mathrm{i}} \qquad (C5.6)$$

Where $\mathrm{Identity}_{0,\mathrm{i}}$ and $\mathrm{Identity}_{1,\mathrm{i}}$ are the conditional coal mining identity values in the base model and the carbon taxation prediction.

When the carbon tax is imposed on the monthly cost,

$$\mathrm{DifProbGeo_i} = 0.0178 + 0.000542\ (1.60)\mathrm{EnvAttitude}_{0,\mathrm{i}} \qquad (C5.7)$$

$$\mathrm{DifProbGeo_i} = 0.0177 + 0.000744\ (2.22)\mathrm{EnvAttitude}_{1,\mathrm{i}} \qquad (C5.8)$$

$$\mathrm{DifProbGeo_i} = 0.0181 + 0.00114\ (3.67)\mathrm{EneAttitude}_{0,\mathrm{i}} \qquad (C5.9)$$

$$\mathrm{DifProbGeo_i} = 0.0181 + 0.00116\ (3.69)\mathrm{EneAttitude}_{1,\mathrm{i}} \qquad (C5.10)$$

The relationship between the difference in probability and environmental attitudes is positive yet not significant for environmental attitude in the base model, but is significant with 95% confidence for environmental attitude when calculated from conditionals in the carbon tax prediction. The relationship between difference in probability and energy-saving attitudes in significant for both set of conditionals.

Repeating this for model X, again, we find that identity is not significantly related to the change in probability of selecting geothermal district heating.

$$\mathrm{DifProbGeo_i} = 0.180 + 0.000243\ (0.63)\mathrm{Identity_{0,i}} \qquad (C5.11)$$

$$\mathrm{DifProbGeo_i} = 0.0322 + 0.0000986\ (0.01)\mathrm{Identity_{1,i}} \qquad (C5.12)$$

Appendix C7: Apollo code for each of the models

C7.1: Model 1 - MNL

```
# ################################################################# #
#### LOAD LIBRARY AND DEFINE CORE SETTINGS                      ####
# ################################################################# #

### Clear memory
rm(list = ls())

### Load libraries
library(apollo)

### Initialise code
apollo_initialise()

### Set core controls
apollo_control    = list(
  modelName       = "MNL_GEMS",
  modelDescr      = "Basic MNL model",
  indivID         = "id",
  outputDirectory = "output")

# ################################################################# #
#### LOAD DATA AND APPLY ANY TRANSFORMATIONS                    ####
# ################################################################# #

database = read.csv("~/Library/CloudStorage/OneDrive-
DurhamUniversity/PhD/Choice Modelling
GEMS/Data/GEMS_full_data_clean_env_080824.csv", header=TRUE)

# ################################################################# #
#### DEFINE MODEL PARAMETERS                                    ####
# ################################################################# #

### Vector of parameters, including any that are kept fixed in
### estimation

apollo_beta=c(asc_geo   = 0,
              asc_hyd   = 0,
              asc_sol   = 0,
              asc_pum   = 0,

              b_invCost = 0,
```

```
              b_monCost = 0,
              b_co2     = 0,
              b_dur     = 0,
              b_job     = 0)

### Vector with names (in quotes) of parameters to be kept fixed
### at their starting value in apollo_beta

apollo_fixed = c("asc_pum")

# ################################################################# #
#### GROUP AND VALIDATE INPUTS                                   ####
# ################################################################# #

apollo_inputs = apollo_validateInputs()

# ################################################################# #
#### DEFINE MODEL AND LIKELIHOOD FUNCTION                        ####
# ################################################################# #

apollo_probabilities=function(apollo_beta,
                              apollo_inputs,
                              functionality="estimate"){

  ### Attach inputs and detach after function exit

  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))

  ### Create list of probabilities P
  P = list()

  ### List of utilities: these must use the same names as in
      mnl_settings, order is irrelevant

  V = list()
  V[["geo"]] = asc_geo   + b_invCost * invCost_1 + b_monCost *
               monCost_1 + b_dur * dur_1 + b_co2 * co2_1 + b_job *
               job_1
  V[["hyd"]] = asc_hyd   + b_invCost * invCost_2 + b_monCost *
               monCost_2 + b_dur * dur_2 + b_co2 * co2_2 + b_job *
               job_2
  V[["sol"]] = asc_sol   + b_invCost * invCost_3 + b_monCost *
               monCost_3 + b_dur * dur_3 + b_co2 * co2_3 + b_job *
               job_3
  V[["pum"]] = asc_pum   + b_invCost * invCost_4 + b_monCost *
               monCost_4 + b_dur * dur_4 + b_co2 * co2_4 + b_job *
               job_4

  ### Define settings for MNL model component
  mnl_settings    = list(
    alternatives  = c(geo=1, hyd=2, sol=3, pum=4),
    choiceVar     = choice,
    utilities     = V)

  ### Compute probabilities using MNL model
```

```
  P[["model"]] = apollo_mnl(mnl_settings, functionality)

  ### Take product across observation for same individual
  P = apollo_panelProd(P, apollo_inputs, functionality)

  ### Prepare and return outputs of function
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)}
# ################################################################# #
#### MODEL ESTIMATION                                            ####
# ################################################################# #

model = apollo_estimate(apollo_beta,
                        apollo_fixed,
                        apollo_probabilities,
                        apollo_inputs)

# ################################################################# #
#### MODEL OUTPUTS                                               ####
# ################################################################# #

apollo_modelOutput(model)
apollo_saveOutput(model)
```

C7.2: Model 2 - MXL

```
# ################################################################# #
#### LOAD LIBRARY AND DEFINE CORE SETTINGS                       ####
# ################################################################# #

### Clear memory
rm(list = ls())

### Load Apollo library
library(apollo)

### Initialise code
apollo_initialise()

### Set core controls
apollo_control    = list(
  modelName       = "MMNL_GEMS",
  modelDescr      = "MMNL model with normal distributions for all
                     attributes on GEMS data",
  indivID         = "id",
  outputDirectory = "output")

# ################################################################# #
#### LOAD DATA AND APPLY ANY TRANSFORMATIONS                     ####
# ################################################################# #

database = read.csv("~/Library/CloudStorage/OneDrive-
DurhamUniversity/PhD/Choice Modelling
GEMS/Data/GEMS_full_data_clean_env_080824.csv", header=TRUE)
```

```
# ################################################################ #
#### DEFINE MODEL PARAMETERS                                    ####
# ################################################################ #

### Vector of parameters, including any that are kept fixed in
### estimation

apollo_beta = c(asc_geo        = 0,
                asc_hyd        = 0,
                asc_sol        = 0,
                asc_pum        = 0,
                b_invCost_mu   = -10,
                b_invCost_sig  = 0,
                b_monCost_mu   = -10,
                b_monCost_sig  = 0,
                b_dur_mu       = 0,
                b_dur_sig      = 0,
                b_co2_mu       = 0,
                b_co2_sig      = 0,
                b_job_mu       = 0,
                b_job_sig      = 0)

### Vector with names (in quotes) of parameters to be kept fixed
### at their starting value in apollo_beta

apollo_fixed = c("asc_pum")

# ################################################################ #
#### DEFINE RANDOM COMPONENTS                                   ####
# ################################################################ #

### Set parameters for generating draws
apollo_draws     = list(
  interDrawsType = "halton",
  interNDraws    = 1000,
  interNormDraws = c("draws_invCost",
                     "draws_monCost",
                     "draws_dur",
                     "draws_co2",
                     "draws_job"))

### Create random parameters
apollo_randCoeff = function(apollo_beta, apollo_inputs){
  randcoeff = list()

  randcoeff[["b_invCost"]] = -exp(b_invCost_mu + b_invCost_sig *
                                  draws_invCost)
  randcoeff[["b_monCost"]] = -exp(b_monCost_mu + b_monCost_sig *
                                  draws_monCost)
  randcoeff[["b_dur"]]     = b_dur_mu + b_dur_sig * draws_dur
  randcoeff[["b_co2"]]     = b_co2_mu + b_co2_sig * draws_co2
  randcoeff[["b_job"]]     = b_job_mu + b_job_sig * draws_job

  return(randcoeff)}
```

```
# ################################################################# #
#### GROUP AND VALIDATE INPUTS                                   ####
# ################################################################# #

apollo_inputs = apollo_validateInputs()

# ################################################################# #
#### DEFINE MODEL AND LIKELIHOOD FUNCTION                        ####
# ################################################################# #


apollo_probabilities = function(apollo_beta,
                                apollo_inputs,
                                functionality="estimate"){

  ### Function initialisation
  ### Attach inputs and detach after function exit
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))

  ### Create list of probabilities P
  P = list()

  ### List of utilities: these must use the same names as in
  ### mnl_settings, order is irrelevant

  V = list()
  V[["geo"]] = (asc_geo  + b_invCost * invCost_1 + b_monCost *
               monCost_1 + b_dur * dur_1 + b_co2 * co2_1 + b_job *
               job_1)
  V[["hyd"]] = (asc_hyd  + b_invCost * invCost_2 + b_monCost *
               monCost_2 + b_dur * dur_2 + b_co2 * co2_2 + b_job *
               job_2)
  V[["sol"]] = (asc_sol  + b_invCost * invCost_3 + b_monCost *
               monCost_3 + b_dur * dur_3 + b_co2 * co2_3 + b_job *
               job_3)
  V[["pum"]] = (asc_pum  + b_invCost * invCost_4 + b_monCost *
               monCost_4 + b_dur * dur_4 + b_co2 * co2_4 + b_job *
               job_4)

  ### Define settings for MNL model component
  mnl_settings    = list(
    alternatives  = c(geo=1, hyd=2, sol=3, pum=4),
    choiceVar     = choice,
    utilities     = V )

  ### Compute probabilities using MNL model
  P[["model"]] = apollo_mnl(mnl_settings, functionality)

  ### Take product across observation for same individual
  P = apollo_panelProd(P, apollo_inputs, functionality)

  ### Average across inter-individual draws
  P = apollo_avgInterDraws(P, apollo_inputs, functionality)

  ### Prepare and return outputs of function
```

```
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)}

# ################################################################# #
#### MODEL ESTIMATION                                            ####
# ################################################################# #

model = apollo_estimate(apollo_beta,
                        apollo_fixed,
                        apollo_probabilities,
                        apollo_inputs)

# ################################################################# #
#### MODEL OUTPUTS                                               ####
# ################################################################# #

apollo_modelOutput(model)
apollo_saveOutput(model)
```

C7.3: Model 3 – MNL with Socio-demographics

```
# ################################################################# #
#### LOAD LIBRARY AND DEFINE CORE SETTINGS                       ####
# ################################################################# #

### Clear memory
rm(list = ls())

### Load libraries
library(apollo)

### Initialise code
apollo_initialise()

### Set core controls
apollo_control    = list(
  modelName       = "MNL_sociodemographics_GEMS_130924",
  modelDescr      = "Sociodemographics MNL model",
  indivID         = "id",
  outputDirectory = "output")

# ################################################################# #
#### LOAD DATA AND APPLY ANY TRANSFORMATIONS                     ####
# ################################################################# #

### Loading data from package
database = read.csv("~/Library/CloudStorage/OneDrive-
DurhamUniversity/PhD/Choice Modelling
GEMS/Data/GEMS_full_data_clean_100924.csv", header=TRUE)

# ################################################################# #
#### DEFINE MODEL PARAMETERS                                     ####
# ################################################################# #
```

```
### Vector of parameters, including any that are kept fixed in
### estimation

apollo_beta = c(asc_geo                   = 0,
                asc_hyd                   = 0,
                asc_sol                   = 0,
                asc_pum                   = 0,

                b_invCost                 = 0,
                b_monCost                 = 0,
                b_co2                     = 0,
                b_dur                     = 0,
                b_job                     = 0,

                a_invCost_low_income      = 0,
                a_monCost_low_income      = 0,
                a_dur_low_income          = 0,
                a_co2_low_income          = 0,
                a_job_low_income          = 0,

                a_invCost_own_accom       = 0,
                a_monCost_own_accom       = 0,
                a_dur_own_accom           = 0,
                a_co2_own_accom           = 0,
                a_job_own_accom           = 0,

                a_invCost_time10          = 0,
                a_monCost_time10          = 0,
                a_dur_time10              = 0,
                a_co2_time10              = 0,
                a_job_time10              = 0,

                a_invCost_exptime10       = 0,
                a_monCost_exptime10       = 0,
                a_dur_exptime10           = 0,
                a_co2_exptime10           = 0,
                a_job_exptime10           = 0,

                a_invCost_male            = 0,
                a_monCost_male            = 0,
                a_dur_male                = 0,
                a_co2_male                = 0,
                a_job_male                = 0,

                a_invCost_uni_ed          = 0,
                a_monCost_uni_ed          = 0,
                a_dur_uni_ed              = 0,
                a_co2_uni_ed              = 0,
                a_job_uni_ed              = 0,

                a_invCost_emp_typ_unemp = 0,
                a_monCost_emp_typ_unemp = 0,
                a_dur_emp_typ_unemp       = 0,
                a_co2_emp_typ_unemp       = 0,
                a_job_emp_typ_unemp       = 0,
```

```
                a_invCost_age35         = 0,
                a_monCost_age35         = 0,
                a_dur_age35             = 0,
                a_co2_age35             = 0,
                a_job_age35             = 0,

                a_invCost_age3555       = 0,
                a_monCost_age3555       = 0,
                a_dur_age3555           = 0,
                a_co2_age3555           = 0,
                a_job_age3555           = 0)

### Vector with names (in quotes) of parameters to be kept fixed
### at their starting value in apollo_beta

apollo_fixed = c("asc_pum")

# ################################################################# #
#### GROUP AND VALIDATE INPUTS                                   ####
# ################################################################# #

apollo_inputs = apollo_validateInputs()

# ################################################################# #
#### DEFINE MODEL AND LIKELIHOOD FUNCTION                        ####
# ################################################################# #

apollo_probabilities = function(apollo_beta,
                                apollo_inputs,
                                functionality="estimate"){

  ### Attach inputs and detach after function exit
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))

  ### Create list of probabilities P
  P = list()

  b_invCost_shift = (b_invCost
                  +  a_invCost_low_income    * low_income
                  +  a_invCost_male          * male
                  +  a_invCost_own_accom     * own_accom
                  +  a_invCost_time10        * time_accom10
                  +  a_invCost_exptime10     * exp_time_accom10
                  +  a_invCost_uni_ed        * uni_ed
                  +  a_invCost_emp_typ_unemp * emp_typ_unemp
                  +  a_invCost_age35         * age35
                  +  a_invCost_age3555       * age3555)

  b_monCost_shift = (b_monCost
                  +  a_monCost_low_income    * low_income
                  +  a_monCost_male          * male
                  +  a_monCost_own_accom     * own_accom
                  +  a_monCost_time10        * time_accom10
                  +  a_monCost_exptime10     * exp_time_accom10
```

```
                + a_monCost_uni_ed          * uni_ed
                + a_monCost_emp_typ_unemp * emp_typ_unemp
                + a_monCost_age35           * age35
                + a_monCost_age3555         * age3555)
b_dur_shift     = (b_dur
                + a_dur_low_income          * low_income
                + a_dur_male                * male
                + a_dur_own_accom           * own_accom
                + a_dur_time10              * time_accom10
                + a_dur_exptime10           * exp_time_accom10
                + a_dur_uni_ed              * uni_ed
                + a_dur_emp_typ_unemp       * emp_typ_unemp
                + a_dur_age35               * age35
                + a_dur_age3555             * age3555)
b_co2_shift     = (b_co2
                + a_co2_low_income          * low_income
                + a_co2_male                * male
                + a_co2_own_accom           * own_accom
                + a_co2_time10              * time_accom10
                + a_co2_exptime10           * exp_time_accom10
                + a_co2_uni_ed              * uni_ed
                + a_co2_emp_typ_unemp       * emp_typ_unemp
                + a_co2_age35               * age35
                + a_co2_age3555             * age3555)
b_job_shift     = (b_job
                + a_job_low_income          * low_income
                + a_job_male                * male
                + a_job_own_accom           * own_accom
                + a_job_time10              * time_accom10
                + a_job_exptime10           * exp_time_accom10
                + a_job_uni_ed              * uni_ed
                + a_job_emp_typ_unemp       * emp_typ_unemp
                + a_job_age35               * age35
                + a_job_age3555             * age3555)

### List of utilities: these must use the same names as in
### mnl_settings, order is irrelevant

V = list()
V[["geo"]] = (asc_geo  + b_invCost_shift * invCost_1 +
              b_monCost_shift * monCost_1 + b_dur_shift * dur_1
              + b_co2_shift * co2_1 + b_job_shift * job_1)
V[["hyd"]] = (asc_hyd  + b_invCost_shift * invCost_2 +
              b_monCost_shift * monCost_2 + b_dur_shift * dur_2
              + b_co2_shift * co2_2 + b_job_shift * job_2)
V[["sol"]] = (asc_sol  + b_invCost_shift * invCost_3 +
              b_monCost_shift * monCost_3 + b_dur_shift * dur_3
              + b_co2_shift * co2_3 + b_job_shift * job_3)
V[["pum"]] = (asc_pum  + b_invCost_shift * invCost_4 +
              b_monCost_shift * monCost_4 + b_dur_shift * dur_4
              + b_co2_shift * co2_4 + b_job_shift * job_4)

### Define settings for MNL model component
mnl_settings    = list(
  alternatives  = c(geo=1, hyd=2, sol=3, pum=4),
  choiceVar     = choice,
```

```
    utilities     = V)

  ### Compute probabilities using MNL model
  P[["model"]] = apollo_mnl(mnl_settings, functionality)

  ### Take product across observation for same individual
  P = apollo_panelProd(P, apollo_inputs, functionality)

  ### Prepare and return outputs of function
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)}
# ################################################################# #
#### MODEL ESTIMATION                                            ####
# ################################################################# #

model = apollo_estimate(apollo_beta,
                        apollo_fixed,
                        apollo_probabilities,
                        apollo_inputs,
                        estimate_settings)

# ################################################################# #
#### MODEL OUTPUTS                                                 ##
# ################################################################# #

apollo_modelOutput(model)
apollo_saveOutput(model)
```

C7.4: Model 4 – MXL with Socio-demographics

```
# ################################################################# #
#### LOAD LIBRARY AND DEFINE CORE SETTINGS                       ####
# ################################################################# #

### Clear memory
rm(list = ls())

### Load libraries
library(apollo)

### Initialise code
apollo_initialise()

### Set core controls
apollo_control    = list(
  modelName       = "MNL_sociodemographics_GEMS",
  modelDescr      = "Sociodemographics MNL model",
  indivID         = "id",
  outputDirectory = "output")

# ################################################################# #
#### LOAD DATA AND APPLY ANY TRANSFORMATIONS                     ####
# ################################################################# #
```

```
database = read.csv("~/Library/CloudStorage/OneDrive-
DurhamUniversity/PhD/Choice Modelling
GEMS/Data/GEMS_full_data_clean_100924.csv", header=TRUE)

# ################################################################ #
#### DEFINE MODEL PARAMETERS                                    ####
# ################################################################ #

### Vector of parameters, including any that are kept fixed in
### estimation

apollo_beta=c(asc_geo                 = 0,
              asc_hyd                 = 0,
              asc_sol                 = 0,
              asc_pum                 = 0,

              b_invCost               = 0,
              b_monCost               = 0,
              b_co2                   = 0,
              b_dur                   = 0,
              b_job                   = 0,

              a_invCost_low_income    = 0,
              a_monCost_low_income    = 0,
              a_dur_low_income        = 0,
              a_co2_low_income        = 0,
              a_job_low_income        = 0,

              a_invCost_own_accom     = 0,
              a_monCost_own_accom     = 0,
              a_dur_own_accom         = 0,
              a_co2_own_accom         = 0,
              a_job_own_accom         = 0,

              a_invCost_male          = 0,
              a_monCost_male          = 0,
              a_dur_male              = 0,
              a_co2_male              = 0,
              a_job_male              = 0,

              a_invCost_uni_ed        = 0,
              a_monCost_uni_ed        = 0,
              a_dur_uni_ed            = 0,
              a_co2_uni_ed            = 0,
              a_job_uni_ed            = 0,

              a_invCost_emp_typ_unemp = 0,
              a_monCost_emp_typ_unemp = 0,
              a_dur_emp_typ_unemp     = 0,
              a_co2_emp_typ_unemp     = 0,
              a_job_emp_typ_unemp     = 0,

              a_invCost_age35         = 0,
              a_monCost_age35         = 0,
              a_dur_age35             = 0,
              a_co2_age35             = 0,
```

```
              a_job_age35            = 0,

              a_invCost_age3555      = 0,
              a_monCost_age3555      = 0,
              a_dur_age3555          = 0,
              a_co2_age3555          = 0,
              a_job_age3555          = 0 )

### Vector with names (in quotes) of parameters to be kept fixed
### at their starting value in apollo_beta

apollo_fixed = c("asc_pum")

# ################################################################# #
#### GROUP AND VALIDATE INPUTS                                   ####
# ################################################################# #

apollo_inputs = apollo_validateInputs()

# ################################################################# #
#### DEFINE MODEL AND LIKELIHOOD FUNCTION                        ####
# ################################################################# #

apollo_probabilities = function(apollo_beta,
                                apollo_inputs,
                                functionality="estimate"){

  ### Attach inputs and detach after function exit

  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))

  ### Create list of probabilities P
  P = list()

  b_invCost_shift = (b_invCost
                  +  a_invCost_low_income    * low_income
                  +  a_invCost_own_accom     * own_accom
                  +  a_invCost_male          * male
                  +  a_invCost_uni_ed        * uni_ed
                  +  a_invCost_emp_typ_unemp * emp_typ_unemp
                  +  a_invCost_age35         * age35
                  +  a_invCost_age3555       * age3555 )
  b_monCost_shift = (b_monCost
                  +  a_monCost_low_income.   * low_income
                  +  a_monCost_own_accom     * own_accom
                  +  a_monCost_male          * male
                  +  a_monCost_uni_ed        * uni_ed
                  +  a_monCost_emp_typ_unemp * emp_typ_unemp
                  +  a_monCost_age35         * age35
                  +  a_monCost_age3555       * age3555 )
  b_dur_shift     = (b_dur
                  +  a_dur_low_income        * low_income
                  +  a_dur_own_accom         * own_accom
                  +  a_dur_male              * male
                  +  a_dur_uni_ed            * uni_ed
```

```
                + a_dur_emp_typ_unemp     * emp_typ_unemp
                + a_dur_age35             * age35
                + a_dur_age3555           * age3555 )
b_co2_shift     = (b_co2
                + a_co2_low_income        * low_income
                + a_co2_own_accom         * own_accom
                + a_co2_male              * male
                + a_co2_uni_ed            * uni_ed
                + a_co2_emp_typ_unemp     * emp_typ_unemp
                + a_co2_age35             * age35
                + a_co2_age3555           * age3555 )
b_job_shift     = (b_job
                + a_job_low_income        * low_income
                + a_job_own_accom         * own_accom
                + a_job_male              * male
                + a_job_uni_ed            * uni_ed
                + a_job_emp_typ_unemp     * emp_typ_unemp
                + a_job_age35             * age35
                + a_job_age3555           * age3555 )

### List of utilities: these must use the same names as in
### mnl_settings, order is irrelevant

V = list()
V[["geo"]] = (asc_geo + b_invCost_shift * invCost_1 +
              b_monCost_shift * monCost_1 + b_dur_shift * dur_1
              + b_co2_shift * co2_1 + b_job_shift * job_1)
V[["hyd"]] = (asc_hyd + b_invCost_shift * invCost_2 +
              b_monCost_shift * monCost_2 + b_dur_shift * dur_2
              + b_co2_shift * co2_2 + b_job_shift * job_2)
V[["sol"]] = (asc_sol + b_invCost_shift * invCost_3 +
              b_monCost_shift * monCost_3 + b_dur_shift * dur_3
              + b_co2_shift * co2_3 + b_job_shift * job_3)
V[["pum"]] = (asc_pum + b_invCost_shift * invCost_4 +
              b_monCost_shift * monCost_4 + b_dur_shift * dur_4
              + b_co2_shift * co2_4 + b_job_shift * job_4)

### Define settings for MNL model component

mnl_settings    = list(
  alternatives  = c(geo=1, hyd=2, sol=3, pum=4),
  choiceVar     = choice,
  utilities     = V )

### Compute probabilities using MNL model
P[["model"]] = apollo_mnl(mnl_settings, functionality)

### Take product across observation for same individual
P = apollo_panelProd(P, apollo_inputs, functionality)

### Prepare and return outputs of function
P = apollo_prepareProb(P, apollo_inputs, functionality)
return(P)}

# ################################################################# #
#### MODEL ESTIMATION                                            ####
```

```
# ################################################################# #

model = apollo_estimate(apollo_beta,
                        apollo_fixed,
                        apollo_probabilities,
                        apollo_inputs,
                        estimate_settings)

# #################################################################
#### MODEL OUTPUTS                                               ####
# ################################################################# #

apollo_modelOutput(model)
apollo_saveOutput(model)
```

C7.5: Model 5a – ICLV with Environmental and Energy Attitudes

```
# #################################################################
#### LOAD LIBRARY AND DEFINE CORE SETTINGS                       ####
#################################################################

### Clear memory
rm(list = ls())

### Load Apollo library
library(apollo)

### Initialise code
apollo_initialise()

### Set core controls
apollo_control    = list(
  modelName       = "Hybrid_with_OL_env_ene_161024",
  modelDescr      = "Hybrid choice model on GEMS data, using
                     ordered measurement model for identity and
                     environmental preference indicators",
  indivID         = "id",
  nCores          = 10,
  outputDirectory = "output")

# #################################################################
#### DEFINE MODEL PARAMETERS                                     ####
#################################################################

### Vector of parameters, including any that are kept fixed in
### estimation

apollo_beta = c(asc_geo                = 0.89,
                asc_hyd                = 0.80,
                asc_sol                = 0.72,
                asc_pum                = 0,
                b_invCost              = -0.9555,
                b_monCost              = -0.7578,
                b_dur                  = 0.3233,
```

```
b_co2                  = -0.7750,
b_job                  = 0.6889,

lambda_env_geo         = 0,
lambda_env_hyd         = 0,
lambda_env_sol         = 0,
lambda_env_inv         = 0,
lambda_env_mon         = 0,
lambda_env_dur         = 0,
lambda_env_co2         = 0,
lambda_env_job         = 0,

lambda_ene_geo         = 0,
lambda_ene_hyd         = 0,
lambda_ene_sol         = 0,
lambda_ene_mon         = 0,
lambda_ene_inv         = 0,
lambda_ene_dur         = 0,
lambda_ene_co2         = 0,
lambda_ene_job         = 0,

gamma_ev_low_income    = 0,
gamma_ev_own_accom     = 0,
gamma_ev_time10        = 0,
gamma_ev_exptime10     = 0,
gamma_ev_male          = 0,
gamma_ev_uni_ed        = 0,
gamma_ev_unemp         = 0,
gamma_ev_age35         = 0,
gamma_ev_age3555       = 0,
gamma_ev_heat_renew    = 0,

gamma_en_low_income    = 0,
gamma_en_own_accom     = 0,
gamma_en_time10        = 0,
gamma_en_exptime10     = 0,
gamma_en_male          = 0,
gamma_en_uni_ed        = 0,
gamma_en_unemp         = 0,
gamma_en_age35         = 0,
gamma_en_age3555       = 0,
gamma_en_heat_renew    = 0,

zeta_conc_env          = 0,
tau_conc_env_1         = -1,
tau_conc_env_2         = -0.5,
tau_conc_env_3         = 0.5,
tau_conc_env_4         = 1,
zeta_change_life       = 0,
tau_change_life_1      = -1,
tau_change_life_2      = -0.5,
tau_change_life_3      = 0.5,
tau_change_life_4      = 1,
zeta_should_change     = 0,
tau_should_change_1    = -1,
tau_should_change_2    = -0.5,
```

```
                tau_should_change_3     = 0.5,
                tau_should_change_4     = 1,
                zeta_adj_therm_know     = 0,
                tau_adj_therm_know_1    = -1,
                tau_adj_therm_know_2    = -0.5,
                tau_adj_therm_know_3    = 0.5,
                tau_adj_therm_know_4    = 1,
                zeta_adj_therm_have     = 0,
                tau_adj_therm_have_1    = -1,
                tau_adj_therm_have_2    = -0.5,
                tau_adj_therm_have_3    = 0.5,
                tau_adj_therm_have_4    = 1,
                zeta_red_energy         = 0,
                tau_red_energy_1        = -1,
                tau_red_energy_2        = -0.5,
                tau_red_energy_3        = 0.5,
                tau_red_energy_4        = 1,
                zeta_energy_dm          = 0,
                tau_energy_dm_1         = -1,
                tau_energy_dm_2         = -0.5,
                tau_energy_dm_3         = 0.5,
                tau_energy_dm_4         = 1)

### Vector with names (in quotes) of parameters to be kept fixed
### at their starting value in apollo_beta

apollo_fixed = c("asc_pum")

### Ben-Akiva normalisation to scale the latent variable set
### coefficient on one of the indicators to 1

# #################################################################
#### DEFINE RANDOM COMPONENTS                                  ####
#################################################################

### Set parameters for generating draws
apollo_draws     = list(
  interDrawsType = "sobolFaureTezuka"
  interNDraws    = 2000,
  interUnifDraws = c(),
  interNormDraws = c("eta2", "eta3"),

  intraDrawsType = "",
  intraNDraws    = 0,
  intraUnifDraws = c(),
  intraNormDraws = c() )

### Create random parameters

apollo_randCoeff=function(apollo_beta, apollo_inputs){
  randcoeff = list()

  randcoeff[["Env_Attitude"]]=(gamma_ev_low_income* low_income
                           + gamma_ev_own_accom * own_accom
                           + gamma_ev_time10    * time_accom10
                           + gamma_ev_exptime10 * exp_time_accom10
```

```
                           + gamma_ev_male      * male
                           + gamma_ev_uni_ed    * uni_ed
                           + gamma_ev_unemp     * emp_typ_unemp
                           + gamma_ev_age35     * age35
                           + gamma_ev_age3555   * age3555
                           + gamma_ev_heat_renew* heat_renew
                           + eta2)

  randcoeff[["Ene_Attitude"]]=(gamma_en_low_income* low_income
                           + gamma_en_own_accom * own_accom
                           + gamma_en_time10    * time_accom10
                           + gamma_en_exptime10 * exp_time_accom10
                           + gamma_en_male      * male
                           + gamma_en_uni_ed    * uni_ed
                           + gamma_en_unemp     * emp_typ_unemp
                           + gamma_en_age35     * age35
                           + gamma_en_age3555   * age3555
                           + gamma_en_heat_renew* heat_renew
                           + eta3)
  return(randcoeff) }

# ################################################################
#### GROUP AND VALIDATE INPUTS                                ####
##################################################################

apollo_inputs = apollo_validateInputs()

# ################################################################
#### DEFINE MODEL AND LIKELIHOOD FUNCTION                     ####
##################################################################

apollo_probabilities = function(apollo_beta,
                                apollo_inputs,
                                functionality="estimate"){

  ### Attach inputs and detach after function exit
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))

  ### Create list of probabilities P
  P = list()

  ### Likelihood of indicators
  ol_settings4 = list(outcomeOrdered= conc_env,
                 V                  = zeta_conc_env*Env_Attitude,
                 tau                = list(tau_conc_env_1,
                                           tau_conc_env_2,
                                           tau_conc_env_3,
                                           tau_conc_env_4),
                 rows               = (choice_no==1),
                 componentName      = "indic_conc_env")

  ol_settings5 = list(outcomeOrdered = change_life,
                 V                = zeta_change_life*Env_Attitude,
                 tau              = list(tau_change_life_1,
                                         tau_change_life_2,
```

```
                                tau_change_life_3,
                                tau_change_life_4),
               rows             = (choice_no==1),
               componentName    = "indic_change_life")

  ol_settings6 = list(outcomeOrdered = should_change,
               V               = zeta_should_change*Env_Attitude,
               tau             = list(tau_should_change_1,
                                    tau_should_change_2,
                                    tau_should_change_3,
                                    tau_should_change_4),
               rows            = (choice_no==1),
               componentName   = "indic_should_change")


  ol_settings7 = list(outcomeOrdered = adj_therm_know,
               V             = zeta_adj_therm_know*Ene_Attitude,
               tau           = list(tau_adj_therm_know_1,
                                  tau_adj_therm_know_2,
                                  tau_adj_therm_know_3,
                                  tau_adj_therm_know_4),
               rows          = (choice_no==1),
               componentName= "indic_adj_therm_know")

  ol_settings8 = list(outcomeOrdered = adj_therm_have,
               V              = zeta_adj_therm_have*Ene_Attitude,
               tau            = list(tau_adj_therm_have_1,
                                   tau_adj_therm_have_2,
                                   tau_adj_therm_have_3,
                                   tau_adj_therm_have_4),
               rows           = (choice_no==1),
               componentName = "indic_adj_therm_have")

  ol_settings9 = list(outcomeOrdered = red_energy,
               V                 = zeta_red_energy*Ene_Attitude,
               tau               = list(tau_red_energy_1,
                                      tau_red_energy_2,
                                      tau_red_energy_3,
                                      tau_red_energy_4),
               rows              = (choice_no==1),
               componentName     = "indic_red_energy")

  ol_settings10 = list(outcomeOrdered = energy_dm,
                V                 = zeta_energy_dm*Ene_Attitude,
                tau               = list(tau_energy_dm_1,
                                       tau_energy_dm_2,
                                       tau_energy_dm_3,
                                       tau_energy_dm_4),
                rows              = (choice_no==1),
                componentName     = "indic_energy_dm")

P[["indic_conc_env"]]= apollo_ol(ol_settings4, functionality)
P[["indic_change_life"]]= apollo_ol(ol_settings5, functionality)
P[["indic_should_change"]]= apollo_ol(ol_settings6, functionality)
P[["indic_adj_therm_know"]]= apollo_ol(ol_settings7,
                                       functionality)
```

```
P[["indic_adj_therm_have"]]= apollo_ol(ol_settings8,
                                        functionality)
P[["indic_red_energy"]]= apollo_ol(ol_settings9, functionality)
P[["indic_energy_dm"]] = apollo_ol(ol_settings10, functionality)


  ### Create alternative specific constants and coefficients using
interactions with latent variables

asc_geo_value   = (asc_geo + lambda_env_geo * Env_Attitude +
                  lambda_ene_geo * Ene_Attitude)
asc_hyd_value   = (asc_hyd + lambda_env_hyd * Env_Attitude +
                  lambda_ene_hyd * Ene_Attitude)
asc_sol_value   = (asc_sol + lambda_env_sol * Env_Attitude +
                  lambda_ene_sol * Ene_Attitude)

b_invCost_value = (b_invCost + lambda_env_inv * Env_Attitude +
                  lambda_ene_inv*Ene_Attitude)
b_monCost_value = (b_monCost + lambda_env_mon * Env_Attitude +
                  lambda_ene_mon*Ene_Attitude)
b_dur_value     = (b_dur + lambda_env_dur * Env_Attitude +
                  lambda_ene_dur*Ene_Attitude)
b_co2_value     = (b_co2 + lambda_env_co2 * Env_Attitude +
                  lambda_ene_co2*Ene_Attitude)
b_job_value     = (b_job + lambda_env_job * Env_Attitude +
                  lambda_ene_job * Ene_Attitude)

  ### Likelihood of choices
  ### List of utilities: these must use the same names as in
  ### mnl_settings, order is irrelevant

V = list()
V[["geo"]] = (asc_geo_value + b_invCost_value * InvCost_1 +
              b_monCost_value * MonCost_1 + b_dur_value * Dur_1 +
              b_co2_value * CO2_1 + b_job_value * Job_1 )
V[["hyd"]] = (asc_hyd_value + b_invCost_value * InvCost_2 +
              b_monCost_value * MonCost_2 + b_dur_value * Dur_2 +
              b_co2_value * CO2_2 + b_job_value * Job_2 )
V[["sol"]] = (asc_sol_value + b_invCost_value * InvCost_3 +
              b_monCost_value * MonCost_3 + b_dur_value * Dur_3 +
              b_co2_value * CO2_3 + b_job_value * Job_3 )
V[["pum"]] = (asc_pum       + b_invCost_value * InvCost_4 +
              b_monCost_value * MonCost_4 + b_dur_value * Dur_4 +
              b_co2_value * CO2_4 + b_job_value * Job_4 )

  ### Define settings for MNL model component
  mnl_settings    = list(
    alternatives  = c(geo=1, hyd=2, sol=3, pum=4),
    avail         = list(geo=1, hyd=1, sol=1, pum=1),
    choiceVar     = choice,
    utilities     = V,
    component     = "choice" )

  ### Compute probabilities for MNL model component
  P[["choice"]] = apollo_mnl(mnl_settings, functionality)
```

```
  ### Likelihood of the whole model
  P = apollo_combineModels(P, apollo_inputs, functionality)

  ### Take product across observation for same individual
  P = apollo_panelProd(P, apollo_inputs, functionality)

  ### Average across inter-individual draws
  P = apollo_avgInterDraws(P, apollo_inputs, functionality)

  ### Prepare and return outputs of function
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P) }

#apollo_beta=apollo_searchStart(apollo_beta,
#apollo_fixed,apollo_probabilities, apollo_inputs)

# ################################################################
#### MODEL ESTIMATION                                         ####
##################################################################

### Estimate model
model = apollo_estimate(apollo_beta, apollo_fixed,
apollo_probabilities, apollo_inputs)

# ################################################################
#### MODEL OUTPUTS                                            ####
##################################################################

apollo_modelOutput(model)
apollo_saveOutput(model)
```

C7.6: Model 5b – ICLV with Environmental and Energy Attitudes MXL

```
# ################################################################
#### LOAD LIBRARY AND DEFINE CORE SETTINGS                    ####
##################################################################

### Clear memory
rm(list = ls())

### Load Apollo library
library(apollo)

### Initialise code
apollo_initialise()

### Set core controls
apollo_control    = list(
  modelName       = "Hybrid_with_OL_env_ene_MXL",
  modelDescr      = "Hybrid choice model on GEMS data, using
                     ordered measurement model for identity and
                     environmental preference indicators",
  indivID         = "id",
  nCores          = 10,
```

```
  outputDirectory = "output")

# ################################################################
#### DEFINE MODEL PARAMETERS                                  ####
##################################################################

### Vector of parameters, including any that are kept fixed in
### estimation

apollo_beta = c(asc_geo     =     0.66966    ,
                asc_hyd     =     0.1376     ,
                asc_sol     =     -0.17367   ,
                asc_pum     =     0     ,
                b_invCost_mu     =     0.71924    ,
                b_invCost_sig    =     1.26374    ,
                b_monCost_mu     =     0.13652    ,
                b_monCost_sig    = 1.05374,
                b_dur_mu     =   0.69666,
                b_dur_sig    =   0.58669,
                b_co2_mu     =   -2.87054,
                b_co2_sig    =   2.39364,
                b_job_mu     =   1.87267,
                b_job_sig    =   2.35984,
                lambda_env_geo  =    -1.33015,
                lambda_env_hyd  =    0.46567,
                lambda_env_sol  =    1.19916,
                lambda_env_inv  =    1.45552,
                lambda_env_mon  =    0.54991,
                lambda_env_dur  =    -0.34919,
                lambda_env_co2  =    1.15929,
                lambda_env_job  =    -1.04404,
                lambda_ene_geo  =    0.44767,
                lambda_ene_hyd  =    0.89473,
                lambda_ene_sol  =    0.34275,
                lambda_ene_mon  =    -0.35352,
                lambda_ene_inv  =    0.04986,
                lambda_ene_dur  =    0.19472,
                lambda_ene_co2  =    -0.78268,
                lambda_ene_job  =    0.10965,
                gamma_ev_low_income =0.02821,
                gamma_ev_own_accom  =0.16332,
                gamma_ev_time10     =-0.0384,
                gamma_ev_exptime10  =0.02188,
                gamma_ev_male       =0.0963,
                gamma_ev_uni_ed     =-0.11492,
                gamma_ev_unemp      =0.10958,
                gamma_ev_age35      =0.27185,
                gamma_ev_age3555    =0.31562,
                gamma_ev_heat_renew =0.28958,
                gamma_en_low_income =-0.22128,
                gamma_en_own_accom  =0.17823,
                gamma_en_time10     =0.01865,
                gamma_en_exptime10  =0.25921,
                gamma_en_male       =0.13879,
                gamma_en_uni_ed     =0.08156,
                gamma_en_unemp      =-0.25341,
```

```
                   gamma_en_age35      =-0.6059,
                   gamma_en_age3555    =-0.22613,
                   gamma_en_heat_renew =-0.34703,
                   zeta_conc_env       =-0.30379,
                   tau_conc_env_1      =-3.94185,
                   tau_conc_env_2      =-2.86504,
                   tau_conc_env_3      =-1.62799,
                   tau_conc_env_4      =0.57441,
                   zeta_change_life    =-0.32087,
                   tau_change_life_1   =-4.05809,
                   tau_change_life_2   =-2.99412,
                   tau_change_life_3   =-1.8175,
                   tau_change_life_4   =0.79812,
                   zeta_should_change  =-0.35936,
                   tau_should_change_1 =-4.14787,
                   tau_should_change_2 =-3.34289,
                   tau_should_change_3 =-1.87381,
                   tau_should_change_4 =0.50068,
                   zeta_adj_therm_know =2.16646,
                   tau_adj_therm_know_1    =  -5.32773,
                   tau_adj_therm_know_2    =  -4.2383,
                   tau_adj_therm_know_3    =  -3.44557,
                   tau_adj_therm_know_4    =  0.03503,
                   zeta_adj_therm_have     =  1.58457,
                   tau_adj_therm_have_1    =  -4.99487,
                   tau_adj_therm_have_2    =  -3.45963,
                   tau_adj_therm_have_3    =  -2.43762,
                   tau_adj_therm_have_4    =  0.6633,
                   zeta_red_energy         =  2.91359,
                   tau_red_energy_1        =  -7.81626,
                   tau_red_energy_2        =  -5.93322,
                   tau_red_energy_3        =  -4.67429,
                   tau_red_energy_4        =  0.22599,
                   zeta_energy_dm          =  1.75068,
                   tau_energy_dm_1        =   -6.02559,
                   tau_energy_dm_2         =  -4.4162,
                   tau_energy_dm_3         =  -2.95351,
                   tau_energy_dm_4         =  -0.23007)
### Vector with names (in quotes) of parameters to be kept fixed
### at their starting value in apollo_beta

apollo_fixed = c("asc_pum")

### Ben-Akiva normalisation to scale the latent variable set
### coefficient on one of the indicators to 1

# ################################################################
#### DEFINE RANDOM COMPONENTS                                 ####
##################################################################

### Set parameters for generating draws
apollo_draws = list(
   interDrawsType="sobolFaureTezuka",
   interNDraws=2000,
   interUnifDraws=c(),
```

```
   interNormDraws=c("eta2", "eta3","draws_invCost","draws_monCost",
"draws_dur", "draws_co2", "draws_job"),

  intraDrawsType = "",
  intraNDraws    = 0,
  intraUnifDraws = c(),
  intraNormDraws = c() )

### Create random parameters

apollo_randCoeff=function(apollo_beta, apollo_inputs){
  randcoeff = list()

  randcoeff[["Env_Attitude"]]=(gamma_ev_low_income* low_income
                             + gamma_ev_own_accom * own_accom
                             + gamma_ev_time10    * time_accom10
                             + gamma_ev_exptime10 * exp_time_accom10
                             + gamma_ev_male      * male
                             + gamma_ev_uni_ed    * uni_ed
                             + gamma_ev_unemp     * emp_typ_unemp
                             + gamma_ev_age35     * age35
                             + gamma_ev_age3555   * age3555
                             + gamma_ev_heat_renew* heat_renew
                             + eta2)

  randcoeff[["Ene_Attitude"]]=(gamma_en_low_income* low_income
                             + gamma_en_own_accom * own_accom
                             + gamma_en_time10    * time_accom10
                             + gamma_en_exptime10 * exp_time_accom10
                             + gamma_en_male      * male
                             + gamma_en_uni_ed    * uni_ed
                             + gamma_en_unemp     * emp_typ_unemp
                             + gamma_en_age35     * age35
                             + gamma_en_age3555   * age3555
                             + gamma_en_heat_renew* heat_renew
                             + eta3)
randcoeff[["b_invCost"]] = -exp(b_invCost_mu + b_invCost_sig *
draws_invCost + b_cor * draws_co2_inv)
randcoeff[["b_monCost"]] = -exp(b_monCost_mu + b_monCost_sig *
draws_monCost)
randcoeff[["b_dur"]] = b_dur_mu + b_dur_sig * draws_dur
randcoeff[["b_co2"]] = b_co2_mu + b_co2_sig * draws_co2
randcoeff[["b_job"]] = b_job_mu + b_job_sig * draws_job + b_cor *
draws_co2_inv
  return(randcoeff) }

# ################################################################
#### GROUP AND VALIDATE INPUTS                               ####
################################################################

apollo_inputs = apollo_validateInputs()

# ################################################################
#### DEFINE MODEL AND LIKELIHOOD FUNCTION                    ####
################################################################
```

```
apollo_probabilities = function(apollo_beta,
                                apollo_inputs,
                                functionality="estimate"){

  ### Attach inputs and detach after function exit
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))

  ### Create list of probabilities P
  P = list()

  ### Likelihood of indicators
  ol_settings4 = list(outcomeOrdered= conc_env,
                      V                  = zeta_conc_env*Env_Attitude,
                      tau                = list(tau_conc_env_1,
                                                tau_conc_env_2,
                                                tau_conc_env_3,
                                                tau_conc_env_4),
                      rows               = (choice_no==1),
                      componentName      = "indic_conc_env")

  ol_settings5 = list(outcomeOrdered = change_life,
                      V                = zeta_change_life*Env_Attitude,
                      tau              = list(tau_change_life_1,
                                              tau_change_life_2,
                                              tau_change_life_3,
                                              tau_change_life_4),
                      rows             = (choice_no==1),
                      componentName    = "indic_change_life")

  ol_settings6 = list(outcomeOrdered = should_change,
                      V              = zeta_should_change*Env_Attitude,
                      tau            = list(tau_should_change_1,
                                            tau_should_change_2,
                                            tau_should_change_3,
                                            tau_should_change_4),
                      rows           = (choice_no==1),
                      componentName  = "indic_should_change")


  ol_settings7 = list(outcomeOrdered = adj_therm_know,
                      V            = zeta_adj_therm_know*Ene_Attitude,
                      tau          = list(tau_adj_therm_know_1,
                                          tau_adj_therm_know_2,
                                          tau_adj_therm_know_3,
                                          tau_adj_therm_know_4),
                      rows         = (choice_no==1),
                      componentName= "indic_adj_therm_know")

  ol_settings8 = list(outcomeOrdered = adj_therm_have,
                      V             = zeta_adj_therm_have*Ene_Attitude,
                      tau           = list(tau_adj_therm_have_1,
                                           tau_adj_therm_have_2,
                                           tau_adj_therm_have_3,
                                           tau_adj_therm_have_4),
                      rows          = (choice_no==1),
```

```
                 componentName = "indic_adj_therm_have")

  ol_settings9 = list(outcomeOrdered = red_energy,
                 V                  = zeta_red_energy*Ene_Attitude,
                 tau                = list(tau_red_energy_1,
                                           tau_red_energy_2,
                                           tau_red_energy_3,
                                           tau_red_energy_4),
                 rows               = (choice_no==1),
                 componentName      = "indic_red_energy")

  ol_settings10 = list(outcomeOrdered = energy_dm,
                  V                  = zeta_energy_dm*Ene_Attitude,
                  tau                = list(tau_energy_dm_1,
                                            tau_energy_dm_2,
                                            tau_energy_dm_3,
                                            tau_energy_dm_4),
                  rows               = (choice_no==1),
                  componentName      = "indic_energy_dm")

P[["indic_conc_env"]]= apollo_ol(ol_settings4, functionality)
P[["indic_change_life"]]= apollo_ol(ol_settings5, functionality)
P[["indic_should_change"]]= apollo_ol(ol_settings6, functionality)
P[["indic_adj_therm_know"]]= apollo_ol(ol_settings7,
                                       functionality)
P[["indic_adj_therm_have"]]= apollo_ol(ol_settings8,
                                       functionality)
P[["indic_red_energy"]]= apollo_ol(ol_settings9, functionality)
P[["indic_energy_dm"]] = apollo_ol(ol_settings10, functionality)


  ### Create alternative specific constants and coefficients using
interactions with latent variables

asc_geo_value   = (asc_geo + lambda_env_geo * Env_Attitude +
                  lambda_ene_geo * Ene_Attitude)
asc_hyd_value   = (asc_hyd + lambda_env_hyd * Env_Attitude +
                  lambda_ene_hyd * Ene_Attitude)
asc_sol_value   = (asc_sol + lambda_env_sol * Env_Attitude +
                  lambda_ene_sol * Ene_Attitude)

b_invCost_value = (b_invCost + lambda_env_inv * Env_Attitude +
                  lambda_ene_inv*Ene_Attitude)
b_monCost_value = (b_monCost + lambda_env_mon * Env_Attitude +
                  lambda_ene_mon*Ene_Attitude)
b_dur_value     = (b_dur + lambda_env_dur * Env_Attitude +
                  lambda_ene_dur*Ene_Attitude)
b_co2_value     = (b_co2 + lambda_env_co2 * Env_Attitude +
                  lambda_ene_co2*Ene_Attitude)
b_job_value     = (b_job + lambda_env_job * Env_Attitude +
                  lambda_ene_job * Ene_Attitude)

  ### Likelihood of choices
  ### List of utilities: these must use the same names as in
  ### mnl_settings, order is irrelevant
```

```
V = list()
V[["geo"]] = (asc_geo_value + b_invCost_value * InvCost_1 +
              b_monCost_value * MonCost_1 + b_dur_value * Dur_1 +
              b_co2_value * CO2_1 + b_job_value * Job_1 )
V[["hyd"]] = (asc_hyd_value + b_invCost_value * InvCost_2 +
              b_monCost_value * MonCost_2 + b_dur_value * Dur_2 +
              b_co2_value * CO2_2 + b_job_value * Job_2 )
V[["sol"]] = (asc_sol_value + b_invCost_value * InvCost_3 +
              b_monCost_value * MonCost_3 + b_dur_value * Dur_3 +
              b_co2_value * CO2_3 + b_job_value * Job_3 )
V[["pum"]] = (asc_pum       + b_invCost_value * InvCost_4 +
              b_monCost_value * MonCost_4 + b_dur_value * Dur_4 +
              b_co2_value * CO2_4 + b_job_value * Job_4 )

  ### Define settings for MNL model component
  mnl_settings    = list(
    alternatives  = c(geo=1, hyd=2, sol=3, pum=4),
    avail         = list(geo=1, hyd=1, sol=1, pum=1),
    choiceVar     = choice,
    utilities     = V,
    component     = "choice" )

  ### Compute probabilities for MNL model component
  P[["choice"]] = apollo_mnl(mnl_settings, functionality)

  ### Likelihood of the whole model
  P = apollo_combineModels(P, apollo_inputs, functionality)

  ### Take product across observation for same individual
  P = apollo_panelProd(P, apollo_inputs, functionality)

  ### Average across inter-individual draws
  P = apollo_avgInterDraws(P, apollo_inputs, functionality)

  ### Prepare and return outputs of function
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P) }

#apollo_beta=apollo_searchStart(apollo_beta,
#apollo_fixed,apollo_probabilities, apollo_inputs)

# ################################################################
#### MODEL ESTIMATION                                         ####
##################################################################

### Estimate model
model = apollo_estimate(apollo_beta, apollo_fixed,
apollo_probabilities, apollo_inputs)

# ################################################################
#### MODEL OUTPUTS                                            ####
##################################################################

apollo_modelOutput(model)
apollo_saveOutput(model)
```

C7.7: Model 5c – ICLV with Environmental and Energy Attitudes MXL with correlation

```
# #################################################################
#### LOAD LIBRARY AND DEFINE CORE SETTINGS                     ####
#################################################################

### Clear memory
rm(list = ls())

### Load Apollo library
library(apollo)

### Initialise code
apollo_initialise()

### Set core controls
apollo_control    = list(
  modelName       = "Hybrid_with_OL_env_ene_MXL_cor",
  modelDescr      = "Hybrid choice model on GEMS data, using
                     ordered measurement model for identity and
                     environmental preference indicators",
  indivID         = "id",
  nCores          = 10,
  outputDirectory = "output")

# #################################################################
#### DEFINE MODEL PARAMETERS                                   ####
#################################################################

### Vector of parameters, including any that are kept fixed in
### estimation

apollo_beta = c(asc_geo    =     0.761971   ,
                asc_hyd    =     0.197592   ,
                asc_sol    =     -0.168279  ,
                asc_pum    =     0     ,
                b_invCost_mu    =     0.737234   ,
                b_invCost_sig   =     -1.013919  ,
                b_monCost_mu    =     0.262974   ,
                b_monCost_sig   =     1.116409   ,
                b_dur_mu   =     0.699838   ,
                b_dur_sig  =     0.613193   ,
                b_co2_mu   =     -2.969189  ,
                b_co2_sig  =     2.297435   ,
                b_job_mu   =     1.924743   ,
                b_job_sig  =     -2.284934  ,
                b_cor      =     0.577071 ,

                lambda_env_geo  =     -1.3144    ,
                lambda_env_hyd  =     0.456004   ,
                lambda_env_sol  =     1.185894   ,
                lambda_env_inv  =     1.397582   ,
                lambda_env_mon  =     0.503376   ,
                lambda_env_dur  =     -0.310334  ,
```

```
lambda_env_co2  =    1.197252  ,
lambda_env_job  =    -1.045922  ,

lambda_ene_geo  =    0.472143  ,
lambda_ene_hyd  =    0.97361   ,
lambda_ene_sol  =    0.42528   ,
lambda_ene_mon  =    -0.321536  ,
lambda_ene_inv  =    0.00629   ,
lambda_ene_dur  =    0.194543  ,
lambda_ene_co2  =    -0.70492  ,
lambda_ene_job  =    0.156987  ,

gamma_ev_low_income  =    0.070444  ,
gamma_ev_own_accom   =    0.157634  ,
gamma_ev_time10 =    -0.078628  ,
gamma_ev_exptime10   =    0.055476  ,
gamma_ev_male   =    0.091241  ,
gamma_ev_uni_ed =    -0.111259  ,
gamma_ev_unemp  =    0.066652  ,
gamma_ev_age35  =    0.33597   ,
gamma_ev_age3555     =    0.335369  ,
gamma_ev_heat_renew  =    0.28424   ,

gamma_en_low_income  =    -0.224146  ,
gamma_en_own_accom   =    0.162904  ,
gamma_en_time10 =    0.017984  ,
gamma_en_exptime10   =    0.282924  ,
gamma_en_male   =    0.123596  ,
gamma_en_uni_ed =    0.073335  ,
gamma_en_unemp  =    -0.226411  ,
gamma_en_age35  =    -0.643717  ,
gamma_en_age3555     =    -0.257897  ,
gamma_en_heat_renew  =    -0.340522  ,

zeta_conc_env   =    -0.324042  ,
tau_conc_env_1  =    -3.964662  ,
tau_conc_env_2  =    -2.887678  ,
tau_conc_env_3  =    -1.649174  ,
tau_conc_env_4  =    0.559275  ,
zeta_change_life     =    -0.351707  ,
tau_change_life_1    =    -4.089524  ,
tau_change_life_2    =    -3.024711  ,
tau_change_life_3    =    -1.845356  ,
tau_change_life_4    =    0.78109   ,
zeta_should_change   =    -0.373905  ,
tau_should_change_1  =    -4.169443  ,
tau_should_change_2  =    -3.364744  ,
tau_should_change_3  =    -1.894839  ,
tau_should_change_4  =    0.484887  ,
zeta_adj_therm_know  =    2.117626  ,
tau_adj_therm_know_1 =    -5.315219  ,
tau_adj_therm_know_2 =    -4.24332  ,
tau_adj_therm_know_3 =    -3.462989  ,
tau_adj_therm_know_4 =    -0.025158  ,
zeta_adj_therm_have  =    1.543307  ,
tau_adj_therm_have_1 =    -4.982673  ,
```

```
                 tau_adj_therm_have_2 =     -3.469168  ,
                 tau_adj_therm_have_3 =     -2.457901  ,
                 tau_adj_therm_have_4 =     0.612349   ,
                 zeta_red_energy =     2.763357   ,
                 tau_red_energy_1      =     -7.587614  ,
                 tau_red_energy_2      =     -5.78483   ,
                 tau_red_energy_3      =     -4.578293  ,
                 tau_red_energy_4      =     0.141731   ,
                 zeta_energy_dm  =     1.736103   ,
                 tau_energy_dm_1 =     -6.04997   ,
                 tau_energy_dm_2 =     -4.451987  ,
                 tau_energy_dm_3 =     -2.998871  ,
                 tau_energy_dm_4 =     -0.280708  )
### Vector with names (in quotes) of parameters to be kept fixed
### at their starting value in apollo_beta

apollo_fixed = c("asc_pum")

### Ben-Akiva normalisation to scale the latent variable set
### coefficient on one of the indicators to 1

# ################################################################
#### DEFINE RANDOM COMPONENTS                                 ####
################################################################

### Set parameters for generating draws
apollo_draws = list(
   interDrawsType="sobolFaureTezuka",
   interNDraws=2000,
   interUnifDraws=c(),
   interNormDraws=c("eta2", "eta3","draws_invCost","draws_monCost",
"draws_dur", "draws_co2", "draws_job", "draws_co2_inv"),

   intraDrawsType="",
   intraNDraws=0,
   intraUnifDraws=c(),
   intraNormDraws=c()       )
### Create random parameters

apollo_randCoeff=function(apollo_beta, apollo_inputs){
  randcoeff = list()

  randcoeff[["Env_Attitude"]]=(gamma_ev_low_income* low_income
                             + gamma_ev_own_accom * own_accom
                             + gamma_ev_time10    * time_accom10
                             + gamma_ev_exptime10 * exp_time_accom10
                             + gamma_ev_male      * male
                             + gamma_ev_uni_ed    * uni_ed
                             + gamma_ev_unemp     * emp_typ_unemp
                             + gamma_ev_age35     * age35
                             + gamma_ev_age3555   * age3555
                             + gamma_ev_heat_renew* heat_renew
                             + eta2)

  randcoeff[["Ene_Attitude"]]=(gamma_en_low_income* low_income
                             + gamma_en_own_accom * own_accom
```

```
                             + gamma_en_time10    * time_accom10
                             + gamma_en_exptime10 * exp_time_accom10
                             + gamma_en_male      * male
                             + gamma_en_uni_ed    * uni_ed
                             + gamma_en_unemp     * emp_typ_unemp
                             + gamma_en_age35     * age35
                             + gamma_en_age3555   * age3555
                             + gamma_en_heat_renew* heat_renew
                             + eta3)
randcoeff[["b_invCost"]] = -exp(b_invCost_mu + b_invCost_sig *
draws_invCost + b_cor * draws_co2_inv)
randcoeff[["b_monCost"]] = -exp(b_monCost_mu + b_monCost_sig *
draws_monCost)
randcoeff[["b_dur"]] = b_dur_mu + b_dur_sig * draws_dur
randcoeff[["b_co2"]] = b_co2_mu + b_co2_sig * draws_co2
randcoeff[["b_job"]] = b_job_mu + b_job_sig * draws_job + b_cor *
draws_co2_inv
  return(randcoeff) }

# ################################################################
#### GROUP AND VALIDATE INPUTS                                 ####
##################################################################

apollo_inputs = apollo_validateInputs()

# ################################################################
#### DEFINE MODEL AND LIKELIHOOD FUNCTION                      ####
##################################################################

apollo_probabilities = function(apollo_beta,
                                apollo_inputs,
                                functionality="estimate"){

  ### Attach inputs and detach after function exit
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))

  ### Create list of probabilities P
  P = list()

  ### Likelihood of indicators
  ol_settings4 = list(outcomeOrdered= conc_env,
                V                  = zeta_conc_env*Env_Attitude,
                tau                = list(tau_conc_env_1,
                                          tau_conc_env_2,
                                          tau_conc_env_3,
                                          tau_conc_env_4),
                rows               = (choice_no==1),
                componentName      = "indic_conc_env")

  ol_settings5 = list(outcomeOrdered = change_life,
                V                = zeta_change_life*Env_Attitude,
                tau              = list(tau_change_life_1,
                                       tau_change_life_2,
                                       tau_change_life_3,
                                       tau_change_life_4),
```

```
               rows              = (choice_no==1),
               componentName     = "indic_change_life")

ol_settings6 = list(outcomeOrdered = should_change,
               V               = zeta_should_change*Env_Attitude,
               tau             = list(tau_should_change_1,
                                      tau_should_change_2,
                                      tau_should_change_3,
                                      tau_should_change_4),
               rows            = (choice_no==1),
               componentName   = "indic_should_change")


ol_settings7 = list(outcomeOrdered = adj_therm_know,
               V             = zeta_adj_therm_know*Ene_Attitude,
               tau           = list(tau_adj_therm_know_1,
                                    tau_adj_therm_know_2,
                                    tau_adj_therm_know_3,
                                    tau_adj_therm_know_4),
               rows          = (choice_no==1),
               componentName= "indic_adj_therm_know")

ol_settings8 = list(outcomeOrdered = adj_therm_have,
               V              = zeta_adj_therm_have*Ene_Attitude,
               tau            = list(tau_adj_therm_have_1,
                                     tau_adj_therm_have_2,
                                     tau_adj_therm_have_3,
                                     tau_adj_therm_have_4),
               rows           = (choice_no==1),
               componentName = "indic_adj_therm_have")

ol_settings9 = list(outcomeOrdered = red_energy,
               V                  = zeta_red_energy*Ene_Attitude,
               tau                = list(tau_red_energy_1,
                                         tau_red_energy_2,
                                         tau_red_energy_3,
                                         tau_red_energy_4),
               rows               = (choice_no==1),
               componentName      = "indic_red_energy")

ol_settings10 = list(outcomeOrdered = energy_dm,
                V                  = zeta_energy_dm*Ene_Attitude,
                tau                = list(tau_energy_dm_1,
                                          tau_energy_dm_2,
                                          tau_energy_dm_3,
                                          tau_energy_dm_4),
                rows               = (choice_no==1),
                componentName      = "indic_energy_dm")

P[["indic_conc_env"]]= apollo_ol(ol_settings4, functionality)
P[["indic_change_life"]]= apollo_ol(ol_settings5, functionality)
P[["indic_should_change"]]= apollo_ol(ol_settings6, functionality)
P[["indic_adj_therm_know"]]= apollo_ol(ol_settings7,
                                       functionality)
P[["indic_adj_therm_have"]]= apollo_ol(ol_settings8,
                                       functionality)
```

```
P[["indic_red_energy"]]= apollo_ol(ol_settings9, functionality)
P[["indic_energy_dm"]] = apollo_ol(ol_settings10, functionality)


  ### Create alternative specific constants and coefficients using
interactions with latent variables

asc_geo_value   = (asc_geo + lambda_env_geo * Env_Attitude +
                  lambda_ene_geo * Ene_Attitude)
asc_hyd_value   = (asc_hyd + lambda_env_hyd * Env_Attitude +
                  lambda_ene_hyd * Ene_Attitude)
asc_sol_value   = (asc_sol + lambda_env_sol * Env_Attitude +
                  lambda_ene_sol * Ene_Attitude)

b_invCost_value = (b_invCost + lambda_env_inv * Env_Attitude +
                  lambda_ene_inv*Ene_Attitude)
b_monCost_value = (b_monCost + lambda_env_mon * Env_Attitude +
                  lambda_ene_mon*Ene_Attitude)
b_dur_value     = (b_dur + lambda_env_dur * Env_Attitude +
                  lambda_ene_dur*Ene_Attitude)
b_co2_value     = (b_co2 + lambda_env_co2 * Env_Attitude +
                  lambda_ene_co2*Ene_Attitude)
b_job_value     = (b_job + lambda_env_job * Env_Attitude +
                  lambda_ene_job * Ene_Attitude)

  ### Likelihood of choices
  ### List of utilities: these must use the same names as in
  ### mnl_settings, order is irrelevant

V = list()
V[["geo"]] = (asc_geo_value + b_invCost_value * InvCost_1 +
              b_monCost_value * MonCost_1 + b_dur_value * Dur_1 +
              b_co2_value * CO2_1 + b_job_value * Job_1 )
V[["hyd"]] = (asc_hyd_value + b_invCost_value * InvCost_2 +
              b_monCost_value * MonCost_2 + b_dur_value * Dur_2 +
              b_co2_value * CO2_2 + b_job_value * Job_2 )
V[["sol"]] = (asc_sol_value + b_invCost_value * InvCost_3 +
              b_monCost_value * MonCost_3 + b_dur_value * Dur_3 +
              b_co2_value * CO2_3 + b_job_value * Job_3 )
V[["pum"]] = (asc_pum       + b_invCost_value * InvCost_4 +
              b_monCost_value * MonCost_4 + b_dur_value * Dur_4 +
              b_co2_value * CO2_4 + b_job_value * Job_4 )

  ### Define settings for MNL model component
  mnl_settings    = list(
    alternatives  = c(geo=1, hyd=2, sol=3, pum=4),
    avail         = list(geo=1, hyd=1, sol=1, pum=1),
    choiceVar     = choice,
    utilities     = V,
    component     = "choice" )

  ### Compute probabilities for MNL model component
  P[["choice"]] = apollo_mnl(mnl_settings, functionality)

  ### Likelihood of the whole model
  P = apollo_combineModels(P, apollo_inputs, functionality)
```

```
  ### Take product across observation for same individual
  P = apollo_panelProd(P, apollo_inputs, functionality)

  ### Average across inter-individual draws
  P = apollo_avgInterDraws(P, apollo_inputs, functionality)

  ### Prepare and return outputs of function
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P) }

#apollo_beta=apollo_searchStart(apollo_beta,
#apollo_fixed,apollo_probabilities, apollo_inputs)

# ################################################################
#### MODEL ESTIMATION                                         ####
##################################################################

### Estimate model
model = apollo_estimate(apollo_beta, apollo_fixed,
apollo_probabilities, apollo_inputs)

# ################################################################
#### MODEL OUTPUTS                                            ####
##################################################################

apollo_modelOutput(model)
apollo_saveOutput(model)
```

C7.8: Model 6a – ICLV with Identity

```
# ################################################################# #
#### LOAD LIBRARY AND DEFINE CORE SETTINGS                      ####
# ################################################################# #

### Clear memory
rm(list = ls())

### Load Apollo library
library(apollo)

### Initialise code
apollo_initialise()

### Set core controls
apollo_control    = list(
  modelName       = "Hydrid choice model identity effect all
                     attributes 05_11 BHHH 100 RD",
  modelDescr      = "Hybrid choice model on GEMS data, using
                     ordered measurement model for identity and
                     environmental preference indicators",
  indivID         = "id",
  nCores          = 10,
  outputDirectory = "output")
```

```
# ################################################################# #
#### LOAD DATA AND APPLY ANY TRANSFORMATIONS                     ####
# ################################################################# #

### Loading data from package
database =
read.csv("/Users/lucyvictorianaga/Library/CloudStorage/OneDrive-
DurhamUniversity/PhD/GEMS/Choice Modelling
GEMS/Data/GEMS_full_data_clean_100924.csv", header=TRUE)

# ################################################################# #
#### DEFINE MODEL PARAMETERS                                     ####
# ################################################################# #

### Vector of parameters, including any that are kept fixed in
### estimation
apollo_beta = c(asc_geo              = 0.91,
                asc_hyd              = 0.81,
                asc_sol              = 0.71,
                asc_pum              = 0,
                b_invCost            = -0.000090,
                b_monCost            = -0.00072,
                b_dur                = 0.029,
                b_co2                = -0.000090,
                b_job                = 0.0057,

                lambda_id_geo        = 0,
                lambda_id_hyd        = 0,
                lambda_id_sol        = 0,

                lambda_id_inv        = 0,
                lambda_id_mon        = 0,
                lambda_id_dur        = 0,
                lambda_id_co2        = 0,
                lambda_id_job        = 0,

                gamma_id_low_income = 0,
                gamma_id_own_accom  = 0,
                gamma_id_time10     = 0,
                gamma_id_exptime10  = 0,
                gamma_id_male       = 0,
                gamma_id_uni_ed     = 0,
                gamma_id_unemp      = 0,
                gamma_id_age35      = 0,
                gamma_id_age3555    = 0,
                gamma_id_no_mines   = 0,

                zeta1_iden_herit    = 1,
                tau1_iden_herit_1   = -2,
                tau1_iden_herit_2   = -1,
                tau1_iden_herit_3   = 1,
                tau1_iden_herit_4   = 2,

                zeta1_hon_his       = 1,
                tau1_hon_his_1      = -2,
                tau1_hon_his_2      = -1,
```

```
            tau1_hon_his_3      = 1,
            tau1_hon_his_4      = 2,

            zeta1_proj_imp      = 1,
            tau1_proj_imp_1     = -2,
            tau1_proj_imp_2     = -1,
            tau1_proj_imp_3     = 1,
            tau1_proj_imp_4     = 2
      )

### Vector with names (in quotes) of parameters to be kept fixed
### at their starting value in apollo_beta

apollo_fixed = c("asc_pum")

### Ben-Akiva normalisation to scale the latent variable set
### coefficient on one of the indicators to 1

# ############################################################## #
#### DEFINE RANDOM COMPONENTS                                 ####
# ############################################################## #

### Set parameters for generating draws
apollo_draws     = list(
  interDrawsType = "sobolFaureTezuka"",
  interNDraws    = 2000,
  interUnifDraws = c(),
  interNormDraws = c("eta"),

  intraDrawsType = "",
  intraNDraws    = 0,
  intraUnifDraws = c(),
  intraNormDraws = c()   )

### Create random parameters
apollo_randCoeff=function(apollo_beta, apollo_inputs){
  randcoeff = list()

  randcoeff[["Identity1"]] = (gamma_id_low_income * low_income
                            + gamma_id_own_accom  * own_accom
                            + gamma_id_time10     * time_accom10
                            + gamma_id_exptime10 *exp_time_accom10
                            + gamma_id_male       * male
                            + gamma_id_uni_ed     * uni_ed
                            + gamma_id_unemp      * emp_typ_unemp
                            + gamma_id_age35      * age35
                            + gamma_id_age3555    * age3555
                            + gamma_id_no_mines   * no_mines
                            + eta)
  return(randcoeff)}

# ############################################################## #
#### GROUP AND VALIDATE INPUTS                                ####
# ############################################################## #

apollo_inputs = apollo_validateInputs()
```

```
# ################################################################# #
#### DEFINE MODEL AND LIKELIHOOD FUNCTION                        ####
# ################################################################# #

apollo_probabilities = function(apollo_beta,
                                apollo_inputs,
                                functionality="estimate"){

  ### Attach inputs and detach after function exit
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))

  ### Create list of probabilities P
  P = list()

  ### Likelihood of indicators
  ol_settings1 = list(outcomeOrdered = iden_herit,
                      V              = zeta1_iden_herit*Identity1,
                      tau            = list(tau1_iden_herit_1,
                                            tau1_iden_herit_2,
                                            tau1_iden_herit_3,
                                            tau1_iden_herit_4),
                      rows           = (choice_no==1),
                      componentName  = "indic1_iden_herit")

  ol_settings2 = list(outcomeOrdered = hon_his,
                     V               = zeta1_hon_his*Identity1 ,
                     tau             = list(tau1_hon_his_1,
                                            tau1_hon_his_2,
                                            tau1_hon_his_3,
                                            tau1_hon_his_4),
                     rows            = (choice_no==1),
                     componentName   = "indic1_hon_his")

  ol_settings3 = list(outcomeOrdered = proj_imp,
                      V              = zeta1_proj_imp*Identity1,
                      tau            = list(tau1_proj_imp_1,
                                            tau1_proj_imp_2,
                                            tau1_proj_imp_3,
                                            tau1_proj_imp_4),
                      rows           = (choice_no==1),
                      componentName  = "indic1_proj_imp")


  P[["indic1_iden_herit"]]= apollo_ol(ol_settings1, functionality)
  P[["indic1_hon_his"]]   = apollo_ol(ol_settings2, functionality)
  P[["indic1_proj_imp"]]  = apollo_ol(ol_settings3, functionality)


  ### Create alternative specific constants and coefficients using
  ### interactions with latent variable

asc_geo_value   = asc_geo   + lambda_id_geo * Identity1
asc_hyd_value   = asc_hyd   + lambda_id_hyd * Identity1
asc_sol_value   = asc_sol   + lambda_id_sol * Identity1
```

```
b_invCost_value = b_invCost + lambda_id_inv * Identity1
b_monCost_value = b_monCost + lambda_id_mon * Identity1
b_dur_value     = b_dur     + lambda_id_dur * Identity1
b_co2_value     = b_co2     + lambda_id_co2 * Identity1
b_job_value     = b_job     + lambda_id_job * Identity1



  ### Likelihood of choices
  ### List of utilities: these must use the same names as in
  ### mnl_settings, order is irrelevant

  V = list()
  V[["geo"]] = (asc_geo_value + b_invCost_value * InvCost_1 +
               b_monCost_value * MonCost_1 + b_dur_value * Dur_1
               + b_co2_value * CO2_1 + b_job_value * Job_1)
  V[["hyd"]] = (asc_hyd_value + b_invCost_value * InvCost_2 +
               b_monCost_value * MonCost_2 + b_dur_value * Dur_2
               + b_co2_value * CO2_2 + b_job_value * Job_2 )
  V[["sol"]] = (asc_sol_value + b_invCost_value * InvCost_3 +
               b_monCost_value * MonCost_3 + b_dur_value * Dur_3
               + b_co2_value * CO2_3 + b_job_value * Job_3 )
  V[["pum"]] = (asc_pum       + b_invCost_value * InvCost_4 +
               b_monCost_value * MonCost_4 + b_dur_value * Dur_4
               + b_co2_value * CO2_4 + b_job_value * Job_4 )

  ### Define settings for MNL model component
  mnl_settings    = list(
    alternatives  = c(geo=1, hyd=2, sol=3, pum=4),
    avail         = list(geo=1, hyd=1, sol=1, pum=1),
    choiceVar     = choice,
    utilities     = V,
    component     = "choice" )

  ### Compute probabilities for MNL model component
  P[["choice"]] = apollo_mnl(mnl_settings, functionality)

  ### Likelihood of the whole model
  P = apollo_combineModels(P, apollo_inputs, functionality)

  ### Take product across observation for same individual
  P = apollo_panelProd(P, apollo_inputs, functionality)

  ### Average across inter-individual draws
  P = apollo_avgInterDraws(P, apollo_inputs, functionality)

  ### Prepare and return outputs of function
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)}

# ################################################################# #
#### MODEL ESTIMATION                                            ####
# ################################################################# #
```

```
### Estimate model
estimate_settings= list(estimationRoutine = "BHHH" )

model = apollo_estimate(apollo_beta, apollo_fixed,
apollo_probabilities, apollo_inputs, estimate_settings)

# ################################################################# #
#### MODEL OUTPUTS                                               ####
# ################################################################# #

apollo_modelOutput(model)
apollo_saveOutput(model)
```

C7.9: Model 6b – ICLV with Identity MXL

```
# ################################################################# #
#### LOAD LIBRARY AND DEFINE CORE SETTINGS                       ####
# ################################################################# #

### Clear memory
rm(list = ls())

### Load Apollo library
library(apollo)

### Initialise code
apollo_initialise()

### Set core controls
apollo_control    = list(
  modelName       = "Hydrid choice model identity effect all
                     attributes 05_11 BHHH 100 RD",
  modelDescr      = "Hybrid choice model on GEMS data, using
                     ordered measurement model for identity and
                     environmental preference indicators",
  indivID         = "id",
  nCores          = 10,
  outputDirectory = "output")

# ################################################################# #
#### LOAD DATA AND APPLY ANY TRANSFORMATIONS                     ####
# ################################################################# #

### Loading data from package
database =
read.csv("/Users/lucyvictorianaga/Library/CloudStorage/OneDrive-
DurhamUniversity/PhD/GEMS/Choice Modelling
GEMS/Data/GEMS_full_data_clean_100924.csv", header=TRUE)

# ################################################################# #
#### DEFINE MODEL PARAMETERS                                     ####
# ################################################################# #

### Vector of parameters, including any that are kept fixed in
```

```
### estimation
apollo_beta = c(asc_geo     =     0.761971   ,
                asc_hyd     =     0.197592   ,
                asc_sol     =     -0.168279  ,
                asc_pum     =     0     ,
                b_invCost_mu     =     0.737234   ,
                b_invCost_sig    =     -1.013919  ,
                b_monCost_mu     =     0.262974   ,
                b_monCost_sig    =     1.116409   ,
                b_dur_mu    =     0.699838   ,
                b_dur_sig =     0.613193   ,
                b_co2_mu    =     -2.969189  ,
                b_co2_sig =     2.297435   ,
                b_job_mu    =     1.924743   ,
                b_job_sig =     -2.284934  ,

                lambda_id_geo     = 1.613,
                lambda_id_hyd     = 0.621,
                lambda_id_sol     = -0.656,
                lambda_id_inv     = -0.903,
                lambda_id_mon     = -0.795,
                lambda_id_dur     = 0.263,
                lambda_id_co2     = -1.026,
                lambda_id_job     = 0.788,

                gamma_id_low_income      =  0.003,
                gamma_id_own_accom       =  -0.092,
                gamma_id_time10          =  0.161,
                gamma_id_exptime10       =  0.056,
                gamma_id_male            =  -0.060,
                gamma_id_uni_ed          =  0.091,
                gamma_id_unemp           =  -0.132,
                gamma_id_age35           =  -0.393,
                gamma_id_age3555         =  -0.261,
                gamma_id_no_mines        =  -0.002,

                zeta1_iden_herit        = -0.097,
                tau1_iden_herit_1       = -2.492,
                tau1_iden_herit_2       = -1.226,
                tau1_iden_herit_3       = 0.043,
                tau1_iden_herit_4       = 1.435,
                zeta1_hon_his           = 0.235,
                tau1_hon_his_1          = -4.164,
                tau1_hon_his_2          = -2.777,
                tau1_hon_his_3          = -0.510,
                tau1_hon_his_4          = 1.450,
                zeta1_proj_imp          = 0.279,
                tau1_proj_imp_1         = -4.330,
                tau1_proj_imp_2         = -3.507,
                tau1_proj_imp_3         = -1.464,
                tau1_proj_imp_4         = 0.649
          )
### Vector with names (in quotes) of parameters to be kept fixed
### at their starting value in apollo_beta

apollo_fixed = c("asc_pum")
```

```
### Ben-Akiva normalisation to scale the latent variable set
### coefficient on one of the indicators to 1

# ################################################################ #
#### DEFINE RANDOM COMPONENTS                                   ####
# ################################################################ #

### Set parameters for generating draws
apollo_draws     = list(
  interDrawsType = "sobolFaureTezuka"",
  interNDraws    = 2000,
  interUnifDraws = c(),
  interNormDraws = c("eta", "draws_invCost", "draws_monCost",
"draws_dur", "draws_co2", "draws_job"),

  intraDrawsType = "",
  intraNDraws    = 0,
  intraUnifDraws = c(),
  intraNormDraws = c()   )

### Create random parameters
apollo_randCoeff=function(apollo_beta, apollo_inputs){
  randcoeff = list()

  randcoeff[["Identity1"]] = (gamma_id_low_income * low_income
                           + gamma_id_own_accom  * own_accom
                           + gamma_id_time10     * time_accom10
                           + gamma_id_exptime10 *exp_time_accom10
                           + gamma_id_male       * male
                           + gamma_id_uni_ed     * uni_ed
                           + gamma_id_unemp      * emp_typ_unemp
                           + gamma_id_age35      * age35
                           + gamma_id_age3555    * age3555
                           + gamma_id_no_mines   * no_mines
                           + eta)
   randcoeff[["b_invCost"]] = -exp(b_invCost_mu + b_invCost_sig *
draws_invCost)
   randcoeff[["b_monCost"]] = -exp(b_monCost_mu + b_monCost_sig *
draws_monCost)
   randcoeff[["b_dur"]] = b_dur_mu + b_dur_sig * draws_dur
   randcoeff[["b_co2"]] = b_co2_mu + b_co2_sig * draws_co2
   randcoeff[["b_job"]] = b_job_mu + b_job_sig * draws_job
  return(randcoeff)}

# ################################################################ #
#### GROUP AND VALIDATE INPUTS                                  ####
# ################################################################ #

apollo_inputs = apollo_validateInputs()

# ################################################################ #
#### DEFINE MODEL AND LIKELIHOOD FUNCTION                       ####
# ################################################################ #

apollo_probabilities = function(apollo_beta,
```

```
                              apollo_inputs,
                              functionality="estimate"){

  ### Attach inputs and detach after function exit
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))

  ### Create list of probabilities P
  P = list()

  ### Likelihood of indicators
  ol_settings1 = list(outcomeOrdered = iden_herit,
                      V              = zeta1_iden_herit*Identity1,
                      tau            = list(tau1_iden_herit_1,
                                            tau1_iden_herit_2,
                                            tau1_iden_herit_3,
                                            tau1_iden_herit_4),
                      rows           = (choice_no==1),
                      componentName  = "indic1_iden_herit")

  ol_settings2 = list(outcomeOrdered = hon_his,
                     V               = zeta1_hon_his*Identity1 ,
                     tau             = list(tau1_hon_his_1,
                                            tau1_hon_his_2,
                                            tau1_hon_his_3,
                                            tau1_hon_his_4),
                     rows            = (choice_no==1),
                     componentName   = "indic1_hon_his")

  ol_settings3 = list(outcomeOrdered = proj_imp,
                      V              = zeta1_proj_imp*Identity1,
                      tau            = list(tau1_proj_imp_1,
                                            tau1_proj_imp_2,
                                            tau1_proj_imp_3,
                                            tau1_proj_imp_4),
                      rows           = (choice_no==1),
                      componentName  = "indic1_proj_imp")


  P[["indic1_iden_herit"]]= apollo_ol(ol_settings1, functionality)
  P[["indic1_hon_his"]]   = apollo_ol(ol_settings2, functionality)
  P[["indic1_proj_imp"]]  = apollo_ol(ol_settings3, functionality)


  ### Create alternative specific constants and coefficients using
  ### interactions with latent variable

asc_geo_value   = asc_geo   + lambda_id_geo * Identity1
asc_hyd_value   = asc_hyd   + lambda_id_hyd * Identity1
asc_sol_value   = asc_sol   + lambda_id_sol * Identity1

b_invCost_value = b_invCost + lambda_id_inv * Identity1
b_monCost_value = b_monCost + lambda_id_mon * Identity1
b_dur_value     = b_dur     + lambda_id_dur * Identity1
b_co2_value     = b_co2     + lambda_id_co2 * Identity1
b_job_value     = b_job     + lambda_id_job * Identity1
```

```
  ### Likelihood of choices
  ### List of utilities: these must use the same names as in
  ### mnl_settings, order is irrelevant

  V = list()
  V[["geo"]] = (asc_geo_value + b_invCost_value * InvCost_1 +
               b_monCost_value * MonCost_1 + b_dur_value * Dur_1
               + b_co2_value * CO2_1 + b_job_value * Job_1)
  V[["hyd"]] = (asc_hyd_value + b_invCost_value * InvCost_2 +
               b_monCost_value * MonCost_2 + b_dur_value * Dur_2
               + b_co2_value * CO2_2 + b_job_value * Job_2 )
  V[["sol"]] = (asc_sol_value + b_invCost_value * InvCost_3 +
               b_monCost_value * MonCost_3 + b_dur_value * Dur_3
               + b_co2_value * CO2_3 + b_job_value * Job_3 )
  V[["pum"]] = (asc_pum       + b_invCost_value * InvCost_4 +
               b_monCost_value * MonCost_4 + b_dur_value * Dur_4
               + b_co2_value * CO2_4 + b_job_value * Job_4 )

  ### Define settings for MNL model component
  mnl_settings    = list(
    alternatives  = c(geo=1, hyd=2, sol=3, pum=4),
    avail         = list(geo=1, hyd=1, sol=1, pum=1),
    choiceVar     = choice,
    utilities     = V,
    component     = "choice" )

  ### Compute probabilities for MNL model component
  P[["choice"]] = apollo_mnl(mnl_settings, functionality)

  ### Likelihood of the whole model
  P = apollo_combineModels(P, apollo_inputs, functionality)

  ### Take product across observation for same individual
  P = apollo_panelProd(P, apollo_inputs, functionality)

  ### Average across inter-individual draws
  P = apollo_avgInterDraws(P, apollo_inputs, functionality)

  ### Prepare and return outputs of function
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)}

# ################################################################ #
#### MODEL ESTIMATION                                          ####
# ################################################################ #

### Estimate model
estimate_settings= list(estimationRoutine = "BHHH" )

model = apollo_estimate(apollo_beta, apollo_fixed,
apollo_probabilities, apollo_inputs, estimate_settings)
```

```
# ################################################################# #
#### MODEL OUTPUTS                                              ####
# ################################################################# #

apollo_modelOutput(model)
apollo_saveOutput(model)
```

C7.10: Model 6c– ICLV with Identity MXL with correlation

```
# ################################################################# #
#### LOAD LIBRARY AND DEFINE CORE SETTINGS                      ####
# ################################################################# #

### Clear memory
rm(list = ls())

### Load Apollo library
library(apollo)

### Initialise code
apollo_initialise()

### Set core controls
apollo_control    = list(
  modelName       = "Hydrid choice model identity effect all
                     attributes 05_11 BHHH 100 RD",
  modelDescr      = "Hybrid choice model on GEMS data, using
                     ordered measurement model for identity and
                     environmental preference indicators",
  indivID         = "id",
  nCores          = 10,
  outputDirectory = "output")

# ################################################################# #
#### LOAD DATA AND APPLY ANY TRANSFORMATIONS                    ####
# ################################################################# #

### Loading data from package
database =
read.csv("/Users/lucyvictorianaga/Library/CloudStorage/OneDrive-
DurhamUniversity/PhD/GEMS/Choice Modelling
GEMS/Data/GEMS_full_data_clean_100924.csv", header=TRUE)

# ################################################################# #
#### DEFINE MODEL PARAMETERS                                    ####
# ################################################################# #

### Vector of parameters, including any that are kept fixed in
### estimation
apollo_beta = c(asc_geo    =    0.761971   ,
                asc_hyd    =    0.197592   ,
                asc_sol    =    -0.168279  ,
                asc_pum    =    0     ,
                b_invCost_mu    =    0.737234   ,
                b_invCost_sig   =    -1.013919  ,
```

```
                b_monCost_mu    =     0.262974   ,
                b_monCost_sig   =     1.116409   ,
                b_dur_mu  =     0.699838   ,
                b_dur_sig =     0.613193   ,
                b_co2_mu  =     -2.969189  ,
                b_co2_sig =     2.297435   ,
                b_job_mu  =     1.924743   ,
                b_job_sig =     -2.284934  ,
                b_cor = 0.5,

                lambda_id_geo    = 1.613,
                lambda_id_hyd    = 0.621,
                lambda_id_sol    = -0.656,
                lambda_id_inv    = -0.903,
                lambda_id_mon    = -0.795,
                lambda_id_dur    = 0.263,
                lambda_id_co2    = -1.026,
                lambda_id_job    = 0.788,

                gamma_id_low_income     =  0.003,
                gamma_id_own_accom      =  -0.092,
                gamma_id_time10         =  0.161,
                gamma_id_exptime10      =  0.056,
                gamma_id_male           =  -0.060,
                gamma_id_uni_ed         =  0.091,
                gamma_id_unemp          =  -0.132,
                gamma_id_age35          =  -0.393,
                gamma_id_age3555        =  -0.261,
                gamma_id_no_mines       =  -0.002,

                zeta1_iden_herit       = -0.097,
                tau1_iden_herit_1      = -2.492,
                tau1_iden_herit_2      = -1.226,
                tau1_iden_herit_3      = 0.043,
                tau1_iden_herit_4      = 1.435,
                zeta1_hon_his          = 0.235,
                tau1_hon_his_1         = -4.164,
                tau1_hon_his_2         = -2.777,
                tau1_hon_his_3         = -0.510,
                tau1_hon_his_4         = 1.450,
                zeta1_proj_imp         = 0.279,
                tau1_proj_imp_1        = -4.330,
                tau1_proj_imp_2        = -3.507,
                tau1_proj_imp_3        = -1.464,
                tau1_proj_imp_4        = 0.649          )
### Vector with names (in quotes) of parameters to be kept fixed
### at their starting value in apollo_beta

apollo_fixed = c("asc_pum")

### Ben-Akiva normalisation to scale the latent variable set
### coefficient on one of the indicators to 1

# ################################################################# #
#### DEFINE RANDOM COMPONENTS                                    ####
# ################################################################# #
```

```
### Set parameters for generating draws
apollo_draws     = list(
  interDrawsType = "sobolFaureTezuka"",
  interNDraws    = 2000,
  interUnifDraws = c(),
  interNormDraws = c("eta", "draws_invCost", "draws_monCost",
"draws_dur", "draws_co2", "draws_job", "draws_job_inv"),

  intraDrawsType = "",
  intraNDraws    = 0,
  intraUnifDraws = c(),
  intraNormDraws = c()   )

### Create random parameters
apollo_randCoeff=function(apollo_beta, apollo_inputs){
  randcoeff = list()

  randcoeff[["Identity1"]] = (gamma_id_low_income * low_income
                            + gamma_id_own_accom  * own_accom
                            + gamma_id_time10     * time_accom10
                            + gamma_id_exptime10 *exp_time_accom10
                            + gamma_id_male       * male
                            + gamma_id_uni_ed     * uni_ed
                            + gamma_id_unemp      * emp_typ_unemp
                            + gamma_id_age35      * age35
                            + gamma_id_age3555    * age3555
                            + gamma_id_no_mines   * no_mines
                            + eta)
   randcoeff[["b_invCost"]] = -exp(b_invCost_mu + b_invCost_sig *
draws_invCost + b_cor * draws_job_inv)
   randcoeff[["b_monCost"]] = -exp(b_monCost_mu + b_monCost_sig *
draws_monCost)
   randcoeff[["b_dur"]] = b_dur_mu + b_dur_sig * draws_dur
   randcoeff[["b_co2"]] = b_co2_mu + b_co2_sig * draws_co2
   randcoeff[["b_job"]] = b_job_mu + b_job_sig * draws_job + b_cor *
draws_job_inv
  return(randcoeff)}

# ############################################################### #
#### GROUP AND VALIDATE INPUTS                                 ####
# ############################################################### #

apollo_inputs = apollo_validateInputs()

# ############################################################### #
#### DEFINE MODEL AND LIKELIHOOD FUNCTION                      ####
# ############################################################### #

apollo_probabilities = function(apollo_beta,
                                apollo_inputs,
                                functionality="estimate"){

  ### Attach inputs and detach after function exit
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))
```

```
### Create list of probabilities P
P = list()

### Likelihood of indicators
ol_settings1 = list(outcomeOrdered = iden_herit,
                    V              = zeta1_iden_herit*Identity1,
                    tau            = list(tau1_iden_herit_1,
                                          tau1_iden_herit_2,
                                          tau1_iden_herit_3,
                                          tau1_iden_herit_4),
                    rows           = (choice_no==1),
                    componentName  = "indic1_iden_herit")

ol_settings2 = list(outcomeOrdered = hon_his,
                   V               = zeta1_hon_his*Identity1 ,
                   tau             = list(tau1_hon_his_1,
                                          tau1_hon_his_2,
                                          tau1_hon_his_3,
                                          tau1_hon_his_4),
                   rows            = (choice_no==1),
                   componentName   = "indic1_hon_his")

ol_settings3 = list(outcomeOrdered = proj_imp,
                    V              = zeta1_proj_imp*Identity1,
                    tau            = list(tau1_proj_imp_1,
                                          tau1_proj_imp_2,
                                          tau1_proj_imp_3,
                                          tau1_proj_imp_4),
                    rows           = (choice_no==1),
                    componentName  = "indic1_proj_imp")


P[["indic1_iden_herit"]]= apollo_ol(ol_settings1, functionality)
P[["indic1_hon_his"]]   = apollo_ol(ol_settings2, functionality)
P[["indic1_proj_imp"]]  = apollo_ol(ol_settings3, functionality)


### Create alternative specific constants and coefficients using
### interactions with latent variable

asc_geo_value   = asc_geo   + lambda_id_geo * Identity1
asc_hyd_value   = asc_hyd   + lambda_id_hyd * Identity1
asc_sol_value   = asc_sol   + lambda_id_sol * Identity1

b_invCost_value = b_invCost + lambda_id_inv * Identity1
b_monCost_value = b_monCost + lambda_id_mon * Identity1
b_dur_value     = b_dur     + lambda_id_dur * Identity1
b_co2_value     = b_co2     + lambda_id_co2 * Identity1
b_job_value     = b_job     + lambda_id_job * Identity1



### Likelihood of choices
### List of utilities: these must use the same names as in
```

```
  ### mnl_settings, order is irrelevant

  V = list()
  V[["geo"]] = (asc_geo_value + b_invCost_value * InvCost_1 +
               b_monCost_value * MonCost_1 + b_dur_value * Dur_1
               + b_co2_value * CO2_1 + b_job_value * Job_1)
  V[["hyd"]] = (asc_hyd_value + b_invCost_value * InvCost_2 +
               b_monCost_value * MonCost_2 + b_dur_value * Dur_2
               + b_co2_value * CO2_2 + b_job_value * Job_2 )
  V[["sol"]] = (asc_sol_value + b_invCost_value * InvCost_3 +
               b_monCost_value * MonCost_3 + b_dur_value * Dur_3
               + b_co2_value * CO2_3 + b_job_value * Job_3 )
  V[["pum"]] = (asc_pum       + b_invCost_value * InvCost_4 +
               b_monCost_value * MonCost_4 + b_dur_value * Dur_4
               + b_co2_value * CO2_4 + b_job_value * Job_4 )

  ### Define settings for MNL model component
  mnl_settings    = list(
    alternatives  = c(geo=1, hyd=2, sol=3, pum=4),
    avail         = list(geo=1, hyd=1, sol=1, pum=1),
    choiceVar     = choice,
    utilities     = V,
    component     = "choice" )

  ### Compute probabilities for MNL model component
  P[["choice"]] = apollo_mnl(mnl_settings, functionality)

  ### Likelihood of the whole model
  P = apollo_combineModels(P, apollo_inputs, functionality)

  ### Take product across observation for same individual
  P = apollo_panelProd(P, apollo_inputs, functionality)

  ### Average across inter-individual draws
  P = apollo_avgInterDraws(P, apollo_inputs, functionality)

  ### Prepare and return outputs of function
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)}

# ################################################################# #
#### MODEL ESTIMATION                                            ####
# ################################################################# #

### Estimate model
estimate_settings= list(estimationRoutine = "BHHH" )

model = apollo_estimate(apollo_beta, apollo_fixed,
apollo_probabilities, apollo_inputs, estimate_settings)

# ################################################################# #
#### MODEL OUTPUTS                                               ####
# ################################################################# #

apollo_modelOutput(model)
apollo_saveOutput(model)
```