The London School of Economics and Political Science

Experiments in Behavioural Environmental Economics

Ganga Shreedhar

July 2018

A thesis submitted to the London School of Economics for the degree of Doctor of Philosophy.

Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated otherwise.

I warrant that this authorisation does not, to the best of my belief, infringe the rights of any third party.

I declare that my thesis consists of 114,105 words.

Statement of conjoint work

I confirm that Chapters 2 and 3 were co-authored with Professor Susana Mourato, at the LSE I contributed 90% of this work. Specifically, I was mainly responsible for the conception, design and implementation of the lab experiment, data analysis, and a vast majority of the writing and editing of the paper. Prof. Mourato had supervisory input in every stage.

I confirm also that Chapter 6 was jointly co-authored with Dr. Alessandro Tavoni of the Grantham Research Institute at LSE and Dr. Carmen Marchiori of the Grantham Research Institute at LSE. I contributed 70% of this work. I conceived of the research idea and proposed the initial experimental design decisions, to which Alessandro gave feedback. I also coded the experiment and implemented it in the lab with Alessandro and Carmen. I was responsible for conducting the data analysis and the majority of the writing.

Statement of prior publication

A version of Chapter 6 was published online as a Grantham Research Institute on Climate Change and the Environment Working Paper No. 292 (Shreedhar, Tavoni and Marchiori, 2018).

Acknowledgements

This thesis is the outcome of a collective process of discovery, involving family, friends, colleagues, institutions, and most certainly my love for nature which has been the intrinsic source of my motivation throughout this journey.

I am grateful to Carmen Marchiori for initially encouraging and supporting me on this path, and Alessandro Tavoni and Susana Mourato for keeping me on it. Your confidence, advice, co-authorship, and friendship have been invaluable and prompted me to keep going in the pursuit of environmental knowledge. I am also grateful to my examiners, Nicholas Hanley and Andries Ritcher, for their insightful and sharp comments.

The Department of Geography and Environment and the Grantham Research Institute have been my intellectual home, these past years, and fantastic colleagues have inspired and motivated me, including Ben Groom, Richard Perkins, Eric Neumayer, Charlie Palmer, Giles Atkinson, Sefi Roth and Olmo Silva. Ginny Pavey and Sam Colegate have been incredibly supportive throughout this journey. I am also fortunate to have benefited from the encouragement and guidance of Matteo Galizzi and Heather Kappes. I am grateful to the LSE and the MPA program for first opening its doors to me.

My peers have been indispensable in many ways. Kate Laffan, Joel Suss, Mara Nogueira and Harry Petit have worked with and alongside me throughout. I also thank others in my cohort for feedback and spirited discussions about our field. A special shout-out to Kjell Eldor for the Planet Earth sessions, Claire Oldfield for helping me on the field, and Ayeesha Sumera, Anushree and Pavandeep Singh for housing me in the other field. All the people I cannot name because I have already overstepped respectable word limits, you know who you are.

Daniel Oldfield has been both a rock and a tree throughout this process, but especially in the final hours, so thank you kindly. I am also grateful to the Oldfields for all your love and support.

I dedicate this thesis to Amma and Appa who have been an unwavering source of love and strength. You were my first teachers, and instilled a love of

all things outdoors and green and taught me to be hopeful that human beings have the potential to change.

Abstract

This thesis investigates what motivates people to protect the environment and protect themselves from environmental risks. Specifically, the essays aim to enhance our understanding of how individual and situational factors drive decision-making in three areas that lie at the heart of behavioural environmental economics: contributions towards protecting public goods like biodiversity, choices under risk from environmental externalities like air pollution, and cooperation over shared common pool resources. The overarching goal of the thesis is to unpack the complex processes behind decision making, to identify policy-relevant mechanisms to promote both planetary and human health and wellbeing. Given this, the essays adopt an experimental approach to study themes like pro-social behaviour, affect, risk preferences, beliefs and social influence, in conjunction with different information and incentive-based interventions.

Paper 1 explores the direct impact of different types of audiovisual information through the charismatic megafauna and outrage effect on contributions to biodiversity conservation. It also signals that mixed emotions could be drivers of pro-sociality in the conservation context. Paper 2 charts the indirect spillover effects of these video interventions on subsequent pro-environmental behavioural intentions. Taken together, the papers highlight the potential of the narratives in videos to encourage public engagement and conservation action to address the sixth mass extinction event.

Papers 3 and 4 explore the psycho-social determinants of avoidance behaviours amongst active travellers, namely cyclists in London. In Paper 3, risk perception rather than risk preferences seem to be a better predictor of avoidance behaviour in the context and sample studied. Domain-specific risk preferences via the willingness to take health risks showed more behavioural validity as regards risk-taking while cycling, and the evidence for cross-context validity was not strong. Paper 4 showed that underlying beliefs about air quality determine how individuals respond to social norm messaging. These results collectively suggest that subjective beliefs about environmental risks influence

individual choice under uncertainty in the context of air pollution avoidance.

Paper 5 explores how the peer monitoring and punishment network structure affects cooperation in a commons dilemma. The results suggest that although free-riders are punished in all networks, incomplete and connected networks elicit lower punishment towards those who deviate less than the socially optimal amount. The complete network elicits more punishment, leaving this network as the least efficient at least in the short-run. Although individuals are initially optimistic about others pro-sociality across networks, beliefs converge to the selfish equilibrium more rapidly in complete networks. The results show that the underlying socio-spatial structure of peer monitoring institutions has welfare implications.

Contents

List of Tables

List of Figures

Chapter 1

Introduction

Two stylized facts characterise the challenges facing humanity and our only home, planet earth. First, we live in an era of multiple environmental crises. We have breached critical ecosystem processes and planetary boundaries that represent safe operating limits for the functioning of the earth. For instance, we are beyond the zone of high uncertainty for biodiversity. The current rate of biodiversity loss, measured through species extinction is estimated to range from 100 to 1000 per million species per year, against the planetary boundary of 10 per million per year. We are also in the zone of uncertainty for climate change. Atmospheric carbon dioxide is estimated at 400 parts per million (ppm) versus the planetary boundary of 350 ppm (Steffen et al., 2015).[1] Second, human behaviour is most likely causing these profound and sweeping global environmental changes. In seeking to recognise this, scientists have called for the period from the Industrial Revolution onwards to be called the 'Anthropocene' to mark the shift to a new geological epoch which is distinct from the Holocene (Zalasiewicz et al., 2011; Steffen et al., 2011).

Understanding and changing human behaviour is critical to addressing these ongoing crises, given our role in precipitating them. Actions to mitigate the ongoing environmental degradation and ecological loss and to adapt to its adverse consequences require consideration. To that end, this thesis investigates people's decisions to protect the environment and protect themselves from environmental risks. Specifically, the essays aim to enhance our understanding of environmental behaviour in three core areas: contributions towards protecting public goods like biodiversity and the environment, choices under risk from

[1] Rockström et al. (2009) define planetary boundaries against values of the control variable set at a 'safe' distance from a dangerous level (for processes without known thresholds at the continental to global scales) or from its global threshold (where thresholds are non-linear transitions in the functioning of coupled human–environmental systems). We are also in the high uncertainty zone about biochemical flows and increasing risk for land-use changes. Around 14 and 150 million tons per year of phosphorous and nitrogen are applied to land as fertiliser each year respectively, as opposed to the planetary boundary of 6.2 and 62 million tons per year for each. The area of forested land as a proportion of forest-covered land before human alteration is 62% and falling versus the planetary boundary of at least 75% (Steffen et al., 2015).

environmental externalities like air pollution, and cooperation over shared common pool resources.

The overarching goal of the thesis is to unpack the complex processes driving individual decision-making in each setting to identify policy-relevant mechanisms to promote human and planetary health, and wellbeing. To do so, each paper in this thesis examines how individual and situational factors influence environmental behaviour, and the role of information and incentive-based interventions, to bring fresh behavioural insights to the settings considered. All the papers adopt an experimental approach, which is the principal method for causal inference in economics. In this way, the thesis hopes to bring causal insights about environmental behaviour in the settings considered to contribute to the field of behavioural environmental economics and environmental policy.

The behavioural environmental economics discipline has witnessed rapid growth over the past decade and has come to fundamentally change the way we conceptualise environmental behaviour. It is an umbrella of approaches that bring insights from the social sciences, especially psychology and sociology, to provide a more realistic - and thereby a more useful - account of decision-making in environmental contexts. However, the application of experimental methods to analyse decision-making in environmental contexts has been integral to changing the way economists view the world more broadly. Consider Kahneman's work documenting bounded rationality through critiques of the stated preference method applied to value public goods like wildlife and decision-making under risk. Or alternatively, Ostrom's investigation of bounded self-interest as evinced in cooperation in the commons. Indeed many have remarked on the early intellectual connections and experimental traditions between environmental and resource economics, and behavioural economics (e.g. in Croson and Treich (2014); List and Price (2016)).

Despite this early 'two-way traffic', more considerable convergence in both fields is needed in areas like contributions to and cooperation over shared natural resources, and choices under environmental risks (Ostrom, 1998; Shogren et al., 2010; Carlsson and Johansson-Stenman, 2012). The five papers in this thesis hope to give a sharper view of the behavioural tendencies that matter by documenting new empirical evidence in three decision contexts that lie at the core of environmental economics: firstly on people's choices to protect and value public goods, secondly on choices under environmental risk, and thirdly on cooperation and social dilemmas over shared natural resources, as described below. For the sake of brevity, Appendix A presents a lengthier literature review that provides historical context to my work, wherein I locate the contributions of this thesis within the broader disciplinary trends in behavioural environmental economics.

I first summarise the overarching aim of this thesis. Then I briefly describe each paper and its contributions, followed by a discussion on the intersecting themes, interventions and experimental methods employed in each paper.

1.1 Research aim

The overarching aim of the thesis is to isolate the causal role of individual and situational factors driving human behaviour in different environmental dilemmas and contexts. It attempts to empirically investigate the causal relationships between these factors by using experimental methods to feed into the design of policy-relevant mechanisms to ultimately promote both human and planetary wellbeing. It is composed of the five papers described below.

1.2 Summary and contributions

Papers 1 and 2 explore contributions towards protecting public goods like biodiversity and the environment, Papers 3 and 4 examine choices under risk from environmental externalities like air pollution, and Paper 5 studies cooperation over shared common pool resources. The main motivations, contributions, and findings of each paper are summarised below. Table 1.1 presents a snapshot of the thesis structure, including the experimental method, themes and interventions used in each paper.

1.2.1 People's choices to protect and value biodiversity and the environment

1.2.1.1 Paper 1: Seeing red, but acting green? Experimental evidence on charitable giving and affect towards biodiversity

Biodiversity is an under-provisioned public good as is evident from the rapid and irreversible sixth mass extinction event (Ceballos et al., 2015). Accounting for the behavioural tendencies in the allocation of resources to conservation can go some way towards filling the unfortunate gap in our understanding of conservation behaviour. These insights are crucial to design effective interventions to scale-up public engagement and financial support for conservation.

Paper 1 examines how charitable giving towards conservation and emotion states varies according to different narratives presented in biodiversity conservation videos, by using a series of lab experiments. It is the first joint exploration of the 'charismatic megafauna effect' and 'outrage effect' on behaviour and emotions in the context of charitable donations.[2] It goes beyond the previous economic and conservation literature on resource allocation towards biodiversity by looking at the causal effects of audio-visual narrative-based content, by using carefully designed video interventions. It also extends existing work by considering the impact of a non-pecuniary incentive, the public recognition of donors, in conjunction with these video interventions and adds to the literature on social image motivations.

Our findings reveal that videos of charismatic Lions increase the likelihood of donating, but not the amount donated conditional on subjects having decided to donate. Conversely, videos with the anthropogenic cause of endangerment increase the amount donated, conditional on deciding to donate, but not the likelihood of donating. Thus while we found that the charismatic megafauna and the outrage effects persist when video interventions were used, they can have distinct impacts on nature of decision-making. We also found that the anthropogenic cause of endangerment causes 'outrage' because it increases a range of mixed emotions including anger and sadness. A practical implication of these results is that video interventions which combine narratives about non-charismatic species with the anthropogenic cause of endangerment could be as fruitful as relying on videos with charismatic species, apart from conveying a more realistic portrait of conservation needs. More broadly, these results suggest that people's choices could be influenced through innovative informational interventions like audio-visual media, and careful attention needs to be paid to the behavioural and emotional reactions their narratives elicit.

1.2.1.2 Paper 2: Do biodiversity conservation videos cause pro-environmental spillover effects?

The potential for audio-visual media as an instrument for behaviour change is clear from Paper 1, and numerous other studies which have studied the causal effect of movie exposure on other behaviours including voting turnout and preferences, fertility choices, and even migration decisions (DellaVigna and La Ferrara, 2015). There is, however, a dearth of evidence on the behavioural impact of both media content and exposure in the conservation domain, especially on subsequent pro-environmental actions that are not targeted

[2] Existing analysis based largely on economic valuation to elicit the willingness to pay (WTP) for conservation, and revealed public expenditure under command and control mechanisms shows a 'charismatic megafauna effect', i.e., resource allocation is higher for charismatic flagships, like lions or pandas, which need not align with their ecological value within that ecosystem (Kontoleon and Swanson, 2003; Richardson and Loomis, 2009; Metrick and Weitzman, 1998). Public WTP is also sensitive to information about intentionally caused ecological harm by humans in CV scenarios, which elicited higher values compared to the damage caused by nature. As people reported feeling more upset and interested, this empirical result was termed the 'outrage effect' (Kahneman et al., 1993).

by conservation videos but may nonetheless be affected.

Paper 2 builds on Paper 1, to map out the potential unintentional spillover effects from video exposure and content (and facing a donation task), on the Willingness to Pay (WTP) a green fee and Willingness to Donate (WTD) time towards environmental causes, by using a companion lab experiment. Unlike previous work, it uses an innovative framework of behavioural spillovers to disentangle the direct and indirect effects of media content and exposure on pro-environmental behaviours. In doing so, it explores how video interventions and undertaking a personally costly pro-environmental behaviour impacts two subsequent pro-environmental behavioural intentions. It adds to the literature on how media impacts environmental and economic behaviour, and behavioural spillovers. It also aims to the further the debate on the mechanisms underpinning behavioural spillovers, by paying attention to the interaction effects between pro-social identity and behavioural similarity.

We found that both media exposure and content had indirect effects on behaviour, apart from the direct effects outlined in Paper 1. Video exposure has a positive spillover effect because it increases the likelihood of a positive WTP green fee for the whole sample. Video content on the anthropogenic cause of endangerment also has a spillover effect as it increases the WTD the amount of time donated for pro-social subjects but not the likelihood of donating. These findings convey that people's pro-environmental preferences and choices are endogenous to past choices and that they can interact with features of the behaviours themselves. It also suggests that organizations can follow up with requests that are similar to past behaviours in future appeals.

1.2.2 People's choices under environmental risks like air pollution

Over 80% of city dwellers live in places where air quality levels were deemed harmful by the World Health Organization (WHO, 2016). In the UK, 59% of the population lives in areas where the level of air pollution is above the legal limits by some estimates (Laville, 2017). Vehicular traffic is a crucial contributor. Keeping in mind that emissions need to be curbed on the supply side, a fundamental question on the demand side is what motivates people to protect themselves by reducing exposure or avoiding air pollution?

Economic research has placed a considerable focus on understanding avoidance behaviour due to its welfare implications. It is conceptualised as a type of preventive health behaviour undertaken by individuals to reduce their exposure to environmental pollutants

(Zivin and Neidell, 2013). Encouraging avoidance through informational approaches is an important policy lever to empower citizens to take better decisions to enhance their health and wellbeing. That said, the bulk of literature on avoidance focuses on the effects of information alerts on extreme pollution or smog days and their behavioural effects on reducing outdoor activity (Zivin and Neidell, 2009; Janke, 2014; Saberian et al., 2017). There is limited research on the 'everyday' avoidance choices taken by individuals to self-protect against daily exposure or the psychological mechanisms underpinning these avoidance decisions, both of which are crucial to painting a more comprehensive picture of individual avoidance behaviour.

1.2.2.1 Paper 3: Taking 'measured' risks while cycling: Field evidence on risk-taking and air pollution avoidance

Paper 3 in Chapter 4 is the first attempt to study risk preferences, and its association with choice in the following two domains: air pollution avoidance and risk-taking while cycling. It uses a lab-in-the-field experiment with a pool of cyclists in London. Hence, it extends the literature on the behavioural validity of risk preferences, which examines, whether different risk preference measures associate with field-based environmental and health behaviours. It is one of the few field-based studies that jointly elicit risk preferences across behavioural domains using different methods, including an incentive-compatible protocol using an ordered lottery selection task, and self-reported willingness to take risks in life and health, and air pollution risk perception, a subjective risk belief. Harnessing insights from the behavioural spillovers literature and Paper 2, a broader range of choices under each behavioural domain is measured to provide a more comprehensive and robust analysis of choice.

The data revealed that only domain-specific risk preferences, i.e., the willingness to take risks in health showed robust correlations with risk-taking behaviour. Furthermore, only air pollution risk perception showed a strong correlation with air pollution avoidance. The results suggest risk preference measures are context-dependent. This implies that researchers could employ protocols more closely aligned with the behavioural domain they are studying in future investigations to draw out empirical associations in the field. Also, risk perception - rather than risk aversion - can induce people to change their avoidance behaviour, marking it out as a valuable policy variable.

1.2.2.2 Paper 4: Optimistic about air quality, but avoiding polluted air? Unpacking the effects of social norm messages

Paper 4 in Chapter 5 is an exploratory paper which builds on the same field study as Paper 3. It supplements the previous paper by considering two new types of subjective beliefs and their relationship with avoidance behaviour: social norms about air pollution avoidance and perceived air quality. Informational interventions that make social norms salient are considered robust behavioural change strategies, yet numerous studies fail to replicate results in new behavioural settings and populations. This raises questions as to how and why responses vary across contexts. Paper 4 adds to this debate because it explores the additional benefits of incorporating social norms in messages over and above basic information on air pollution health risks and avoidance options. The paper also considers a fast growing avoidance option used by active travellers in the outdoors, namely anti-pollution facemasks.

The results show that treatment effects were heterogeneous: individuals who held more optimistic beliefs about air quality in London because they perceived air quality was better, were more likely to choose face-masks when exposed to the social norms message. These results bring to light the under-examined role of prior beliefs about environmental risks - in this case about air quality - as a possible explanation for why social norms messaging may induce behaviour change amongst some individuals but not others.

1.2.3 People's choices to cooperate over common pool resources

The management of shared common pool resources is a continuing struggle: around 90% of the world's fish stocks are now fully or overfished and a 17% increase in production is forecast by 2025, with adverse environmental, food and livelihood security implications (FAO, 2016). A policy question in the face of these challenges whether governments should focus on strengthening local institutions, like peer monitoring, which can support cooperation. Somewhat surprisingly, there is less research on peer punishment in non-linear CPR appropriation dilemmas, and existing work primarily investigates perfect peer sanctioning institutions, i.e., everyone can monitor and punish each other.

1.2.3.1 Paper 5: The effects of imperfect monitoring and punishment networks in a common pool resource dilemma

Like Paper 4, Paper 5 in Chapter 6 also looks at social influence but through a different analytical lens. It explores how the socio-spatial structure of monitoring and punishment networks impact appropriation, punishment, and beliefs about other's appropriation in a common pool resource (CPR) game, by using a lab experiment. It adds to the literature on decentralised management of the commons analysed through the framework of social dilemmas, especially on peer sanctioning, by the novel application of different network architectures. Also, it extends the literature on the impact of network interactions on cooperation by paying attention to how beliefs over others' appropriation evolve in systematically different ways because of variations in the network structure.

We found that despite the fact that individuals start off more pro-social (and expect others to be more pro-social as well), peer punishment was unable to prevent free-riding in any of the networks considered, although free-riders (i.e., those who appropriate above the Pareto optimal level) were sanctioned in all networks. Welfare was lower in perfect networks because of the higher incidence of punishment used and because connected but incomplete networks elicited lower punishment for those who appropriated less than the Pareto optimal level. Lastly, the difference between beliefs and others' appropriation declined faster in the complete network, relative to incomplete but connected networks. The results show that underlying variations in the network architecture of peer monitoring institutions affect welfare, punishment behaviour and the evolution of beliefs about other's pro-sociality.

Table 1.1: Summary of methods, themes and interventions

Papers		Paper 1	Paper 2	Paper 3	Paper 4	Paper 5
Method		Lab	Lab	Field	Field	Lab
Themes	Affect	x				
	Pro-sociality	x	x			x
	Behavioural spillovers		x	x		
	Risk preferences			x	x	
	Beliefs			x	x	x
	Social influence					x
Interventions	Information	x	x	-	x	x
	Incentives	x	-	-	-	x

[a] The types of pro-sociality considered are as follows; Paper 1: charitable donations; Paper 2: charitable donations, willingness to pay a green fee, and willingness to donate time; Paper 5: appropriation in the common pool and costly punishment to reduce appropriation.
[b] The types of information interventions considered are as follows; Paper 1 and Paper 2: audio-visual media/videos; Paper 4: text + graphic; Paper 5: Monitoring feedback (of other's appropriation decisions in the network).
[c] The types of incentive interventions considered are as follows; Paper 1: public recognition; Paper 5: (personally) costly peer punishment.
[d] Papers 1 and 2 are companion papers from a series of lab-experiments. Papers 3 and 4 are companion papers from a lab-in-the-field experiment.

1.3 Notes on intersecting themes and methods

Table 1.1 outlines the intersecting conceptual themes running through this thesis, which includes pro-sociality towards the environment and humans, experienced affect, behavioural spillovers, beliefs about the environment and human behaviour, and finally social influence through social norms and network interactions. Informational and incentive-based interventions are intertwined with the themes. Audio-visual information (conservation videos) are studied in relation to pro-sociality, affect and behavioural spillovers, messages incorporating text and graphics are designed keeping social influence in mind, and the network structure determines information feedback. Public recognition seeks to harness individuals' social image motivations, and peer punishment opportunities are derived from network interactions. The intersecting themes and interventions are located within each paper briefly below.

1.3.1 Intersecting themes

Different types of pro-social behaviour, i.e., when individuals act to promote the interests of others rather than their material interests in contradiction to the predictions of the rational model of self-interest, are considered primarily as outcome variables. For example, charitable donations, WTP green fee, WTD time in Papers 1 and 2, and reduced appropriations and pro-social punishment in Paper 5 are all types of pro-social behaviour. Attention is also paid to different types of subjective beliefs held by individuals both as explanatory variables in Paper 3 (air pollution health risks), and Paper 4 (social norms around avoidance taken by others), and as an outcome variable in Paper 5 (other's expected appropriation from the CPR). Other individual-level factors investigated experienced affect as a reaction to different types of audio-visual content in Paper 1, and risk preferences as an explanatory variable in Paper 5. Finally, pro-environmental behavioural spillovers are estimated in Paper 2 and used to motivate the research design and analysis in Paper 3. The impact of social influence on behaviour is studied in Paper 4 through social norms messaging, and in Paper 5 through analysing the effects of peer monitoring and punishment network interactions.

1.3.2 Notes on interventions

The behaviourally informed informational interventions are as follows. In Paper 1 and 2, exposure to carefully designed biodiversity conservation videos are exogenously varied as regards their content about charismatic and non-charismatic species, a compound habitat composed of the two, and the anthropogenic cause of endangerment. While video content is varied in Paper 1, both video content and exposure are varied in Paper 2. In Paper

4, subjects are exposed to textual and graphic information about air pollution risks and face-masks or an identical (treatment) message augmented with social norms. In Paper 5, the type of monitoring and punishment network exogenously determines the feedback that other group members receive about others' appropriation behaviour. Regarding incentives, Paper 1 offers the non-pecuniary incentive of publicly recognising donors. Paper 5 changes the socio-spatial incentive environment through distinctions in the network architecture which defines the punishment opportunities available to group members. Each paper discusses the behavioural interventions in more detail.

1.3.3 Notes on experimental methods

Papers 1, 2 and 5 used lab experiments, and Paper 3 and 4 used a lab-in-the-field experiment. The choice of experimental method for each is discussed below, and each paper presents a more detailed discussion of the same.

1.3.4 Lab experiments

Papers 1 and 2 tested the affective and behavioural impact of video exposure and content using a series of lab experiments. Lab experiments were deemed as a suitable starting point to explore these impacts for many reasons. Firstly, an alternative was to use self-reported before and after data through longitudinal surveys to measure changes in behaviour and affect in natural locations like movie theatres. However, results from this method are possibly confounded by sample selection bias, concerns over self-reported data, and interviewer demand as reviewed by Howell (2014) in greater detail. Another option was to exploit naturally occurring exogenous variations, e.g. in the roll-out of TV programs, to estimate causal effects, as done in other studies on the economic impacts of media (assuming that the necessary assumptions hold) (DellaVigna and La Ferrara, 2015). But obtaining exogenous variation on specific types of media content as opposed to media exposure is very challenging using this approach. More broadly, existing conservation videos did not systematically vary narrative content to test the behavioural tendencies that we had in mind. Moreover, while such quasi-experimental effects can reveal causal effects on behaviour, impacts of emotions are much harder to measure because they tend to rely on self-reports or bio-physical data, which are easier to collect in the lab.

Similarly, Paper 5 tests the causal effects of different socio-spatial institutions on behaviour (appropriation, punishment) and beliefs (expected extraction) also using a lab experiment. An alternative would have been to use observational and survey data from the field to look at real resource outcomes as in Rustagi et al. (2010) and real-world social networks as in Bodin and Crona (2008). But individuals navigate multiple types of relationships (e.g. family, ethnic, religious, friendship, monitoring and punishment) which complicates causal inference. The mosaic of inter-personal connections reflects Ostrom (2006)'s concern that the simultaneous occurrence of many variables in a given field setting increases the uncertainty about the causal effect of a specific variable (or a limited set of variables) on an outcome.

1.3.5 Lab-in-the-field experiment

Paper 3 and 4 move from the lab into the field. They used a lab-in-the-field experiment, which is defined by Gneezy and Imas (2017) as a method that 'combines elements of both lab and field experiments in using standardised, validated paradigms from the lab in targeting relevant populations in naturalistic settings'.[3] Moving from the lab to the field confers two main advantages. It allows us to move beyond non-student populations, and access less artificial environments than the lab, both of which are of policy-interest in the context of the papers considered. In addition, the lab-in-the-field protocol is especially useful to elicit individual preferences using experimental methods because it retains a degree of control due to the use of the lab-validated paradigm.

More broadly, lab and lab-in-the-field experiments are essential methodological tools in an experimental researcher's arsenal because they allow the researcher to generate and take responsibility for data to test a specific hypothesis in a relatively controlled environment to enhance internal validity. Importantly, they can be replicated across multiple contexts and field sites at a relatively low cost. Replication can take the form of re-analysing the data, reproducing the experimental design in a new setting with different subjects, as well as varying the experimental parameters to check for the effects of design-level factors. Given the novel nature of the interventions examined, it was useful to take the first step to test-bed their impact in the lab first before going into the field. Each paper discusses the experimental method and design employed in more detail, alongside its potential limitations.

[3]This corresponds broadly to Harrison and List (2004)'s description of artefactual field experiment as 'the same as a conventional lab experiment but with a non-standard subject pool'. I follow Gneezy and Imas (2017) in the argument that the physical location of the lab is not what defines a method, and laboratory experiments that are run outside of the university are not best described as field experiments.

1.4 Notes on the thesis structure

Each of the five papers is written as an independent piece so that the thesis can be read in any order. However, Paper 2 extends the findings of Paper 1. Similarly, Paper 4 extends the research in Paper 3. Both sets of papers also share a common experimental design and data collection procedure. Given this, there is some overlap in the experimental methods section between Papers 1 and 2, and between Papers 3 and 4. I have attempted to minimise this overlap as much as possible without compromising the integrity of each paper.

Each paper has it's own data appendix which can include methodological and conceptual notes, the full specifications of the empirical models in the main text, and robustness checks. To avoid replication, Appendix G jointly provides supplementary materials for Papers 1 and 2, and Appendix H combines the supplementary materials for Papers 3 and 4. The supplementary materials for Paper 5 are provided in Appendix I.

Bibliography

Bodin, Ö. and Crona, B. I. (2008). Management of natural resources at the community level: exploring the role of social capital and leadership in a rural fishing community. *World development*, 36(12):2763–2779.

Carlsson, F. and Johansson-Stenman, O. (2012). Behavioral economics and environmental policy. *Annu. Rev. Resour. Econ.*, 4(1):75–99.

Ceballos, G., Ehrlich, P. R., Barnosky, A. D., García, A., Pringle, R. M., and Palmer, T. M. (2015). Accelerated modern human–induced species losses: Entering the sixth mass extinction. *Science advances*, 1(5):e1400253.

Croson, R. and Treich, N. (2014). Behavioral environmental economics: promises and challenges. *Environmental and Resource Economics*, 58(3):335–351.

DellaVigna, S. and La Ferrara, E. (2015). Economic and social impacts of the media. In *Handbook of media economics*, volume 1, pages 723–768. Elsevier.

FAO (2016). The state of world fisheries and aquaculture. http://www.fao.org/3/a-i5555e.pdf [Access date: April 2017].

Gneezy, U. and Imas, A. (2017). Lab in the field: Measuring preferences in the wild. In *Handbook of economic field experiments*, volume 1, pages 439–464. Elsevier.

Harrison, G. W. and List, J. A. (2004). Field experiments. *Journal of Economic literature*, 42(4):1009–1055.

Howell, R. A. (2014). Investigating the long-term impacts of climate change communications on individuals' attitudes and behavior. *Environment and Behavior*, 46(1):70–101.

Janke, K. (2014). Air pollution, avoidance behaviour and children's respiratory health: Evidence from england. *Journal of health economics*, 38:23–42.

Kahneman, D., Ritov, I., Jacowitz, K. E., and Grant, P. (1993). Stated willingness to pay for public goods: A psychological perspective. *Psychological science*, 4(5):310–315.

Kontoleon, A. and Swanson, T. (2003). The willingness to pay for property rights for the giant panda: can a charismatic species be an instrument for nature conservation? *Land Economics*, 79(4):483–499.

Laville, S. (2017). https://www.theguardian.com/environment/2017/apr/22/nearly-40-million-people-live-in-uk-areas-with-illegal-air-pollution [Accessed date: 23 March 2018].

List, J. A. and Price, M. K. (2016). The use of field experiments in environmental and resource economics. *Review of Environmental Economics and Policy*, 10(2):206–225.

Metrick, A. and Weitzman, M. L. (1998). Conflicts and choices in biodiversity preservation. *Journal of Economic Perspectives*, 12(3):21–34.

Ostrom, E. (1998). A behavioral approach to the rational choice theory of collective action: Presidential address, american political science association, 1997. *American political science review*, 92(1):1–22.

Ostrom, E. (2006). The value-added of laboratory experiments for the study of institutions and common-pool resources. *Journal of Economic Behavior & Organization*, 61(2):149–163.

Richardson, L. and Loomis, J. (2009). The total economic value of threatened, endangered and rare species: an updated meta-analysis. *Ecological Economics*, 68(5):1535–1548.

Rockström, J., Steffen, W., Noone, K., Persson, Å., Chapin III, F. S., Lambin, E., Lenton, T. M., Scheffer, M., Folke, C., Schellnhuber, H. J., et al. (2009). Planetary boundaries: exploring the safe operating space for humanity. *Ecology and society*, 14(2).

Rustagi, D., Engel, S., and Kosfeld, M. (2010). Conditional cooperation and costly monitoring explain success in forest commons management. *science*, 330(6006):961–965.

Saberian, S., Heyes, A., and Rivers, N. (2017). Alerts work! air quality warnings and cycling. *Resource and Energy Economics*, 49:165–185.

Shogren, J. F., Parkhurst, G. M., and Banerjee, P. (2010). Two cheers and a qualm for behavioral environmental economics. *Environmental and Resource Economics*, 46(2):235–247.

Steffen, W., Grinevald, J., Crutzen, P., and McNeill, J. (2011). The anthropocene: conceptual and historical perspectives. *Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*, 369(1938):842–867.

Steffen, W., Richardson, K., Rockström, J., Cornell, S. E., Fetzer, I., Bennett, E. M., Biggs, R., Carpenter, S. R., De Vries, W., de Wit, C. A., et al. (2015). Planetary boundaries: Guiding human development on a changing planet. *Science*, 347(6223):1259855.

WHO (2016). Who global urban ambient air pollution database. http://www.who.int/phe/health_topics/outdoorair/databases/cities/en/ [Accessed: 23 January 2018].

Zalasiewicz, J., Williams, M., Haywood, A., and Ellis, M. (2011). The anthropocene: a new epoch of geological time?

Zivin, J. G. and Neidell, M. (2009). Days of haze: Environmental information disclosure and intertemporal avoidance behavior. *Journal of Environmental Economics and Management*, 58(2):119–128.

Zivin, J. G. and Neidell, M. (2013). Environment, health, and human capital. *Journal of Economic Literature*, 51(3):689–730.

Chapter 2

Seeing red, but acting green? Experimental evidence on charitable giving and affect towards biodiversity

2.1 Introduction

Drawing public attention to the rapid human-induced loss of biodiversity to boost support and funding for conservation is the need of the hour. The average rate of vertebrate species loss over the past 100 years is 100 times higher than the historical background rate of 2 mammal extinctions per 10,000 species (Ceballos et al., 2015). Funding shortfalls are a barrier to increasing the scope and scale of current conservation efforts (Ceballos et al., 2017; Dirzo et al., 2014; Butchart et al., 2010): illustratively, one estimate is that only 12% of the estimated cost of reducing the extinction risk of threatened bird species is currently funded (McCarthy et al., 2012). Unfortunately, we know less about people's resource allocation choices towards biodiversity conservation. Our existing knowledge is derived primarily from the economic valuation literature and analysis of public expenditures under command and control mechanisms.[1]

A striking empirical pattern emerges: both the public willingness to pay (WTP) for biodiversity conservation and state and federal spending on conservation is higher for habitats with charismatic megafauna (Richardson and Loomis, 2009; Metrick and Weitzman, 1998).[2] However, this pattern, which has been called the 'charismatic megafauna effect' (Metrick and Weitzman, 1998), need not align with ecological criteria for biodiversity preservation which often includes other priorities like the number and type of species or the genetic variability in a given area. In seeking to understand why these patterns persist, researchers across disciplines like economics, psychology and geography have remarked that the feelings that people harbour towards species are essential psychological drivers of decisions to protect them (Metrick and Weitzman, 1998; Lorimer, 2007).

This empirical trend has also led conservation organisations to rely extensively on charismatic megafauna, especially big cats, in public outreach and funding appeals. The principal argument for this strategy is that they generate more public funding and support which can be deployed for the conservation of less charismatic species and the broader biodiversity habitat in which they live (Macdonald et al., 2015; Caro and Riggio, 2013; Sergio et al., 2008). Others are concerned about the unintended adverse effects of this approach, such as the decreased attractiveness and public acceptance of non-flagship species, increased risk of ex situ conservation for charismatic species, and 'flagship fatigue' which may reduce giving in the long-run (Douglas and Winkel, 2014; Lindenmayer et al., 2002; Sitas et al., 2009; Clucas et al., 2008; Kontoleon and Swanson, 2003; Bowen-Jones

[1] Please refer to Helm and Hepburn (2012) for a comprehensive overview of the economic analysis of biodiversity.

[2] Charismatic megafauna or 'flagships' are commonly large, popular vertebrates associated with a particular habitat, like Lions from the African savanna (Clucas et al., 2008), Leader-Williams and Dublin (2000), and Verissimo et al. (2011).

and Entwistle, 2002). Underlying this debate is the worrying dynamic of the continuing marginalisation of non-charismatic but ecologically relevant species from the conservation and research agenda, as observed from the allocation of public expenditures towards species conservation (Metrick and Weitzman, 1998; Dawson and Shogren, 2001).

How robust are these empirical patterns? Do these behavioural patterns reveal themselves in other contexts like charitable giving? These issues beg the broader question: what motivates people to act pro-socially through choices to protect threatened species and their habitats? How can we design interventions to increase pro-social behaviours, like charitable giving?

This paper aims to address these questions. It explores the causal effect of different types of audiovisual information or the narrative content in brief biodiversity conservation videos on charitable giving and affect, by using a series of lab experiments. Study 1 focuses on charitable donations behaviour. Subjects are exposed to videos featuring either a non-charismatic species (Bats) or a charismatic species (Lions) or a biodiversity habitat composed of both charismatic and non-charismatic species living in it (Bats and Lions in the Savanna habitat), after which they can choose to allocate money to a conservation charity. Thus, our first contribution is to extend empirical evidence on the charismatic megafauna effect, by examining its robustness in the donations context using video interventions.

Our second contribution is to verify the 'outrage effect' in this setting. The outrage effect refers to the classic albeit under-explored finding that people's WTP to undo the environmental harm caused by humans is higher than if the same harm was caused by nature (Kahneman et al., 1993; Bulte et al., 2005). Kahneman et al. (1993) coined the term to capture the underlying affective processes that potentially motivated this economic behaviour, on the basis that people reported feeling more upset upon hearing about the human action was the root cause of adverse environmental outcomes. To test the robustness of this finding, we augment each video with audiovisual information on the anthropogenic cause of endangerment and map changes in donations behaviour from exposure to this additional media content.

In addition to this, we also tested the behavioural impact of a non-pecuniary incentive through the offer to publicly recognise donors. This is a real-world strategy frequently used by conservation organisations to increase citizen engagement through combining informational strategies with non-pecuniary incentives (e.g. publishing their names in newsletters). Thus the third contribution of this study is to check if such incentives yield additional benefits through increased donations when used in conjunction with videos.

Study 2 builds on Study 1, and explores the role of affect as a possible motivational force in driving donations behaviour. Subjects reported affective responses to being exposed to the same videos used earlier. Hence, our fourth contribution is to disentangle the affective basis of the charismatic megafauna and outrage effects by looking at changes in a wider set of discrete positive and negative states of affect that are experienced by individuals. In doing so, we present new evidence about how audiovisual information about biodiversity conservation could elicit mixed emotional reactions in public audiences and flag some possible channels through which donations behaviour may be influenced.

Exploring the effects of videos is particularly expedient at this current moment. Conservation and news organisations increasingly rely on audio-visual mass media such as online videos, documentaries, and photographs to raise financial resources and garner policy support. This strategy harnesses the growing public proclivity to obtain information about environmental issues from digital platforms and social media (Stamm et al., 2000; Gavin and Marshall, 2011; Sakellari, 2015; Painter et al., 2018). To illustrate, YouTube has over a billion users amounting to almost one-third of all people on the Internet and over half the views come from mobile devices (YouTube, 2018). Many existing videos tend to give prominence to charismatic megafauna and sometimes include conservation relevant information, such as the ecological role of the species and its endangerment status. They often omit to mention the anthropogenic cause of endangerment and the role of humans in hastening the sixth mass extinction. While some feel such videos encourage conservation behaviour, others have expressed unease about these narratives because they may breed complacency about our destruction of the planet (Hughes-Games, 2017). Well-documented evidence on the behavioural responses to these videos can help further these debates.

Audiovisual media can change behaviour through different pathways like providing new information, changing preferences, and altering emotion states, and different types of narrative content can exert separate impacts on economic behaviour and experienced affect (Moyer-Gusé, 2008; La Ferrara, 2016; Nicholson-Cole, 2005). For example, La Ferrara (2016) notes media can provide new information or provide specific narratives about an issue, which in turn can induce individuals to update their beliefs, or revise their preferences over a given course of action. Nicholson-Cole (2005) observes that the use of emotive imagery and narratives are especially fruitful in attracting people's attention. Merchant et al. (2010) notes that charitable organisations use storytelling to provide a case for public support by taking individuals through different (mixed) emotional stages, to induce them to donate to reduce negative affect or to act on feelings of empathy. Going further, Kemp et al. (2012) observe that charitable fund-raising efforts aim to elicit mixed emotion states because they elicit more extensive behavioural intentions than appeals based only on the generation of negative emotions. Ruth et al. (2002) observe that advertisements generating high levels of positive and negative emotions, are processed more carefully by viewers and hence are regarded as more interesting, and 'prepares individuals for action'. These potential pathways of influence suggest that the effect of narrative content can work towards promoting biodiversity conservation. However, the impact of different types of media content used in biodiversity conservation videos on charitable donations and experienced affect is empirically unclear at present, and jointly eliciting its effects on behaviour and affect is the overarching focus and contribution of this paper.

Our findings show that the charismatic megafauna and the outrage effects persist when video interventions are used on charitable donations behaviour, but that they have distinct effects on decision-making. More precisely, videos of charismatic Lions increase the likelihood of donating, but not the amount donated conditional on subjects having decided to donate. Conversely, videos with the anthropogenic cause of endangerment increase the amount donated conditional on deciding to donate, but not the likelihood of donating. We also found that the anthropogenic cause of endangerment causes 'outrage' and an increase in a range of mixed emotions including anger and sadness. The broader implication of this result is that innovative informational interventions like brief videos can positively impact conservation behaviour, so careful attention needs to be paid to the narratives and stories presented in them and the emotional and behavioural reactions they elicit in audiences.

The rest of the paper is organised as follows: the next section locates the current research in related literature, and section 3 outlines the experimental design and the procedures used. Section 4 presents the results and section 5 concludes with a discussion.

2.2 Related literature

Below, is a review of four strands of literature: on patterns of resource allocations to charismatic megafauna and biodiversity habitats primarily from economic valuation studies and public expenditure data, studies on the willing to pay to correct anthropogenic environmental problems problems, studies on social image motivations and public recognition in relation to charitable giving, and finally on affect towards charismatic megafauna and nature, as well as the outrage effect.

2.2.1 Charismatic megafauna, habitats and resource allocation

We make several contributions to the existing research on biodiversity conservation. First, we add to the literature on how species charisma impacts the allocation of financial resources towards protection (Metrick and Weitzman, 1996, 1998; Loomis and White, 1996; Bulte and Van Kooten, 1999; Dawson and Shogren, 2001; Kontoleon and Swanson, 2003; Christie et al., 2006; Martín-López et al., 2007; Marešová and Frynta, 2008; Richardson and Loomis, 2009; Morse-Jones et al., 2012; Tisdell et al., 2007, 2006). Metrick and Weitzman (1996) and Metrick and Weitzman (1998) are influential papers, which studied revealed behaviour towards charismatic and non-charismatic species through the allocation of federal expenditures under the Endangered Species Act in the United States of America. They found charismatic species (proxied by size and taxonomy) attracted more funding and policy support (also see Dawson and Shogren (2001) and Brown and Shogren (1998)). Stated preferences studies using contingent valuation (e.g. Kontoleon and Swanson (2003)) and choice experiments (e.g. Jacobsen et al. (2008), Morse-Jones et al. (2012) and Richardson and Loomis (2009)), also found charismatic flagships elicited a higher stated Willingness To Pay (WTP) or donate to conservation programs. We extend this literature by measuring individual's revealed pro-social behaviour using an charitable giving game with monetary stakes.

Currently, limited empirical evidence quantifies the relative benefits of using charismatic flagships in donation appeals, relative to non-charismatic species or habitats (Sitas et al., 2009; Clucas et al., 2008). To the best of our knowledge, only Thomas-Walters and J Raihani (2017) used a charitable giving game to quantify individual differences in giving from exposure to combined photo-cum-text appeals featuring charismatic (polar bear, tiger, Asian elephant) and non-charismatic species (dusky gopher frog, North Atlantic cod, Western glacier stonefly), across different habitats. They found average donations to charismatic species were marginally higher than to non-charismatic species amongst Amazon Mechanical Turk workers (USD 0.16 versus USD 0.13). Taking this insight further, we examine if differences in pro-sociality from exposure to various species persists when individuals are exposed to brief conservation videos in Study 1. Furthermore, we attempt to control for underlying differences in the habitat of charismatic and non-charismatic species by considering charismatic and non-charismatic species within the same habitat.[3]

[3]Differences in underlying habitats may affect donations if subjects are more likely to donate a higher amount to more favourable biomes or habitats. For example, forest and tundra biomes have been found to elicit more favourable rankings of preferences, scenic beauty, and restorative effects, compared to desert or grassland biomes (Han, 2007; Falk and Balling, 2010). Similarly, individuals report feeling happier outdoors in all green or natural habitat types, especially coastal areas, than in urban environments (MacKerron and Mourato, 2013).

Second, we investigate whether using a charismatic species alongside a non-charismatic species within the same biodiversity habitat influences pro-sociality. In related literature, Hsee and Rottenstreich (2004) and Thomas-Walters and J Raihani (2017), found donations are not significantly different between one and many recipients of the same species. But Markowitz et al. (2013) reported that non-environmentalists stated lower hypothetical donation amounts when presented with many recipients of the same species although environmentalists do not. Keeping in mind these mixed results, we examine donations towards a habitat composed of different species (biological diversity) instead of many individuals of the same species (biological resource).[4] From the stated preference literature, Jacobsen et al. (2008) investigate some of these issues using a choice experiment to assess preferences over the preservation of the Danish heath and its endangered species. They found that the WTP to conserve this habitat was significantly higher when two (lesser known) species were 'iconised' by explicitly naming them, compared to a quantitative description of the habitat. We build on this work, by comparing whether naming one charismatic and non-charismatic species changes donations behaviour, compared to appeals featuring a single species.[5] By doing so, we hope to shed light on how the scale of biocomplexity may impact pro-social behaviour to ultimately feed into the behavioural design of conservation policies (Mainwaring, 2001).

2.2.2 Anthropogenic cause of endangerment and resource allocation

Third, we examine how media content on the anthropogenic cause of endangerment impacts pro-social behaviour towards conservation. Economic models of behaviour assume that individuals care only about outcomes and not their causes (Ashraf et al., 2005; Bulte et al., 2005). But in contingent valuation studies, individuals stated a higher WTP when information about the human-made causes of environmental problems is made available

[4] Curiously, the mixed results on the difference in giving to a single versus many non-human victims, contrasts with the well-established 'identifiable victim effect', i.e., an individual human recipient (e.g. one refugee child) elicits higher donations than many human recipients (Jenni and Loewenstein, 1997; Västfjäll et al., 2014). An implication of this, is that findings from experimental studies of pro-sociality towards human recipients need not carry over to non-human species and the natural world.

[5] Our work also potentially connects to discussions on embedding and scope effects in the contingent valuation (CV) literature. Kahneman and Knetsch (1992) and Desvousges et al. (1993) argue that respondents to CV surveys are willing to spend a particular amount of money on a good, regardless of it's scale, which is an important characteristic of the good being valued. While methodological innovations like split sample tests are one way to address this, scope insensitivity may persist in situations where an environmental program can provide multiple outputs - like protecting different endangered species in a biodiversity habitat. As noted by Carson (2012), it is difficult to obtain distinct WTP estimates for the individual species or outputs as opposed to the entire program in such cases. We do not address issues of scope sensitivity in the current study, as we consider charitable donations (often used as a payment vehicle in CV studies) rather than WTP for a particular conservation program. See Carson (2012) for a review of these issues.

(Bulte et al., 2005; Brown et al., 2002; Kahneman and Ritov, 1994; Kahneman et al., 1993). For instance, Bulte et al. (2005) found WTP to protect seals is significantly higher when they appear to be threatened by an act of humankind (oil and gas drillers, greenhouse effect) rather than nature. Kahneman et al. (1993) call this empirical finding the 'outrage effect' because individuals reported they would feel more 'upset' if they were to read a story or watch an item on television about man-made environmental problems rather those arising from natural causes (they also rated man-made problems as more 'important'; Kahneman et al. (1993).[6] We contribute to this literature by considering if additional audio-visual media content on the anthropogenic cause of biodiversity depletion (through hunting and illegal wildlife trade) impacts revealed pro-sociality, controlling for background conservation-relevant information. This acts as a robustness check to examine whether increased pro-sociality persists in this new experimental set-up; i.e., a different human-cause of endangerment (hunting), informational medium (videos), and an incentive-compatible rather than stated behaviour (revealed charitable donations).

2.2.3 Social image motivations, public recognition and pro-sociality

We also build on the empirical finding that people behave more pro-socially in public rather than in private. This observation is supported by theoretical models of moral behaviour that propose that an individual's revealed pro-sociality is motivated by the need to maintain a moral image and identity, to signal to themselves and others that they adhere to the 'right' and 'good' norms prevalent in society (Bénabou and Tirole, 2006, 2011; Harbaugh, 1998). Lab and field experiments find that public visibility and recognition of donors is a non-pecuniary incentive to increase giving (Ariely et al., 2009; Karlan and McConnell, 2014; Cotterill et al., 2013; Lacetera and Macis, 2010). For example, Karlan and McConnell (2014) found that charitable giving is higher when donor names are published in funding circle newsletters.[7] Conversely, other studies show that incentives aiming to provide additional benefits to the individual from acting generously can 'crowd-out' pro-sociality and lead to either no effect or a reduction in giving instead (Bowles and Polania-Reyes, 2012; Irlenbusch and Ruchala, 2008; Cardenas et al., 2000; Gneezy and Rustichini, 2000). For example, in Irlenbusch and Ruchala (2008), low bonuses did

[6] Bulte et al. (2005) critically differentiate between the outrage effect which is attributable to the human-made cause of environmental degradation, and responsibility effects which relates people's WTP to the degree of responsibility that they personally feel for the outcome. In the latter case, as noted by Brown et al. (2002) attributing the case to another entity (e.g. a corporation) will lower the general public's WTP, possibly even below WTP if the loss were caused by a natural process. In our experiment, we only test the outrage effect, not the responsibility effect.

[7] This is more broadly in keeping with studies which observe that giving in experimental games can be fragile, and contingent on the contextual and institutional features of the experimental task, such as public visibility. For example, Dana et al. (2007) and Dana et al. (2006) show that individuals act less generously when dictators are given the option to keep their decisions shielded from the receiver, even at a personal cost to themselves.

not affect contributions in a public goods game. Although high bonuses increased contributions, the amounts contributed by subjects were not significantly different from the prediction for self-interested individuals. This result showed that in a social dilemma, both the offer and magnitude of an incentive that conferred personal benefit could exert an unexpected effect on behaviour (also see Bowles (2008)). We complement this work by examining whether the offer of public recognition as a non-pecuniary incentive increases pro-sociality towards biodiversity when used in conjunction with audio-visual informational strategies.

2.2.4 Affect towards charismatic megafauna and outrage

Lastly, we contribute to the literature on the relationship between affect, charisma, and conservation. Although numerous studies from ecological economics, psychology and conservation have noted that emotional responses to biodiversity (and wildlife more generally) matter for conservation choices, empirical and experimental evidence on the topic is scarce. For instance, Metrick and Weitzman (1998) noted that 'the utility of each species/library will be measured as a combination of commercial, recreational and, yes, emotional reactions to a given species.' Lorimer (2007) observed that 'affect' provided the vital motivating force that compels people to get involved in conservation, and that animals 'dramatically other to us humans' (less charismatic species) are far less likely to engender sympathetic affections, based on qualitative evidence. Other studies found that charismatic species are rated as more 'likeable' (Tisdell et al., 2005), more 'appealing' (Brambilla et al., 2013) and that they can inspire more fondness, emotional affinity and 'caring' attitudes (Brown and Shogren, 1998; Ballantyne et al., 2007; Skibins et al., 2013).[8]

Theoretically, the 'Biophilia' hypothesis proposes that emotional responses towards natural stimuli play a central role in explaining humankind's innate connection with the natural world (Kellert and Wilson, 1995). Kellert and Wilson (1995) proposed that individuals can have inherent emotionally laden negativistic attitudes, such as fear and aversion, towards species like snakes, spiders and bats, which in turn can determine broader wildlife attitudes and value orientations (also see Knight (2008). Subsequent research recognizes the evolutionary basis for such emotional reactions, but goes further by proposing that negative emotional responses towards specific species are a result of socio-cultural conditioning, knowledge, contextual features (e.g. if animals are in zoos versus the

[8] Another strand of literature notes that differences in legal rights exist between non-charismatic species (e.g. rats are not considered 'animals' by animal welfare law) and familiar charismatic species (e.g. dogs are often treated like friends or family members) and proposes that 'moral heuristics' are crucial explanatory factors (e.g. 'Rats are pests: pests are bad' versus 'Don't betray friends and family') (Herzog and Burghardt, 2005; Sunstein and Nussbaum, 2004).

wild) and/or a combination of all these factors (Öhman and Mineka, 2003; Jacobs, 2009; Lorimer, 2007).[9] More broadly, there is growing experimental evidence that emotions or 'visceral factors' influence economic and moral decision-making (Loewenstein, 2000; Slovic et al., 2007; Keltner and Lerner, 2010). For instance, the 'affect heuristic' proposed by Slovic et al. (2007) propounds that emotional responses towards objects, which occur rapidly and automatically, can guide decision-making by substituting for systematic cognitive assessments. This corresponds to dual systems theories of decision-making, which differentiate between emotional and heuristics drive System 1 and deliberative processing in System 2 as mechanisms that motivate behaviour (Kahneman, 2003; Camerer et al., 2005).[10]

We contribute to this literature by attempting to quantify the causal impact of content in biodiversity conservation videos on different types of affect. As a core aspect of experienced affect is valence (i.e., 'positive' or 'negative', and 'good' or 'bad'; Cornelius (1996); Slovic et al. (2007)), we attempt to isolate a range of positive and negative affective states from videos with charismatic and non-charismatic species, and a biodiversity habitat consisting of both in Study 2. We also aim to disentangle the affective basis of 'the outrage effect' discussed in Kahneman et al. (1993) who restrict their efforts to measuring ratings of 'upset' and 'importance'. Related work on the 'outrage heuristic' proposes that responses to perceived wrongdoing inculcate a sharp sense of outrage, which in turn influences people's judgements of punishment for the wrongdoing (Kahneman et al., 1998; Kahneman and Frederick, 2002; Sunstein et al., 2008). We extend this work by investigating the role of biodiversity conservation videos in increasing moral outrage, by providing information about the human causes of biodiversity loss in a salient and memorable manner. Specifically, we attempt to map potential changes to a series of positive and negative affective states to disentangle the emotional basis of the outrage effect, given that previous research has demonstrated it holds behavioural consequences.[11].

[9]These contextual factors may also include the nativity of species: for example, Lundhede et al. (2014) found Danish citizens had a higher WTP for the conservation of birds currently native to Denmark, than for bird species moving into the country.

[10]Related work explores the role of emotion-based moral satisfaction driving the willingness to pay to correct environmental problems (Kahneman and Knetsch, 1992). Similarly, the 'warm glow' from charitable giving or the utility that one obtains from the act of giving without any concern about the interests of others (Andreoni, 1989, 1990) has also been investigated. We do not attempt to measure this construct in the present study, but see (Konow, 2010) for an novel effort to do so.

[11]In this paper, we focus on the role of 'integral emotions', i.e., the experience of emotions like anger or sadness, which occur at the moment of decision and are directly related to the decision at hand - in our case, these emotions are stimulated through the video appeal to donate. These are distinct from 'anticipated emotions' from the outcome of the decision itself (e.g. the expectation of happiness of seeing the Savanna preserved compared to the expected happiness of buying a book, both of which materialize at some future point), or 'incidental' emotions, which may occur at the moment of a choice decision, but are unrelated to the payoffs from the decision at hand (Rick and Loewenstein, 2008). These different categories of emotion (apart from the type of emotion experienced) can arguably impact revealed and stated choices in distinct ways: for example, Hanley et al. (2017) found incidental emotions did not affect

2.3 Experimental procedure and design

The overarching objective of Study 1 is to examine how audiovisual narrative content on charismatic and / or non-charismatic species and habitats, and the anthropogenic cause of endangerment drive charitable giving, to check for the 'charismatic megafauna' and 'outrage' effects. Study 2, builds on Study 1 to assess whether the same audiovisual content on charismatic and / or non-charismatic species and habitats, and the anthropogenic cause of endangerment, elicits particular emotion states. While we cannot conclude that the potential change in affective states in Study 2 drives empirical patterns of charitable giving in Study 1, a joint and systematic exploration of donations and emotions from the same audiovisual information allows us to flag changes in affective states as a possible driver of behaviour to explored in the future. The experimental procedure, interventions and study design are explained below.

2.3.1 Procedure

Experimental sessions for Study 1 on Donations and Study 2 on Affect were held from 16 November to 08 December 2016, at the London School of Economics Behavioural Research Lab (LSE BRL). Participation was open to all individuals registered at the LSE BRL, to ensure an adequate sample size for all treatments. A total of 564 subjects participated, where 377 subjects participated in Study 1 and 177 subjects in Study 2. Both Study 1 and 2 were conducted simultaneously on the same days. Each session lasted for 20 minutes on average, and could hold a maximum of 20 subjects (the number of subjects per session ranged from 5 to 20). Each subjects were randomly assigned to a computer terminal upon entering the lab, after which the computer program randomly assigned them to one of the treatments in either Study 1 or Study 2. Thus, the randomization was at the individual-level for each session. The experimental survey was hosted on Qualtrics.

The experimental procedure in Study 1 was as follows: after consenting to participate, subjects watched a video and made their donation decision. Next, they answered questions measuring affect followed by questions on pro-environmental and pro-social behaviour, socio-economic and demographic characteristics. After this, subjects could collect their payments. All subjects were paid £5 for participation and could earn a maximum of £25 from the charitable giving task. But only one subject from each session was selected at

willingness to pay for changes in coastal water quality and fish populations in New Zealand (discussed in greater detail in Chapter 3) random to receive the pay-out from the charitable giving game. The experimental procedure was identical in Study 2, barring the absence of the donations task, and the payment was restricted to the £5 participation fee. The supplementary materials are available in Appendix G.

2.3.2 Biodiversity conservation videos

As existing videos were not designed to provide information in a controlled manner, we constructed conservation videos using a sequence of photos and a scripted voice-over. We used the International Union for the Conservation of Nature red list database and began our search by habitat, threat classification, and conservation status.[12] We chose the lion and the bat, both of which live in the Savanna habitat, as charismatic and non-charismatic species respectively., both of which live in the Savanna habitat. This case-based comparative approach, i.e., measuring individual's behavioural and attitudinal differences between charismatic and non-charismatic species, follows standard methods used previously in the ecological economics and psychology literature (e.g. in Christie et al. (2006) and Tisdell and Nantha (2006)).

Bats are associated with unfavourable symbolic values and generate negative affective states such as disgust, fear, and phobias across cultures (Kingston, 2016; Knight, 2008; Kahn Jr et al., 2008). Although bat populations have also suffered a severe decline, this phenomenon has received less attention even in scientific circles (Fleming and Bateman, 2016). Furthermore, previous studies demonstrated that subjects have lower WTP to pay for bats (Martín-López et al., 2007). Lions are a popular, charismatic flagship commonly used on donation appeals, with populations in West, Central, and East Africa likely to suffer a projected 50% decline over the next two decades (Bauer et al., 2015; Macdonald et al., 2015). Both bats and lions are found in the Savanna, which is a policy-relevant biodiversity habitat projected to experience a severe reduction in species richness (Newbold et al., 2015). Both bats and lions in the Savanna face endangerment from common anthropogenic factors such as hunting, and illegal wildlife trade, which are unambiguous human threats (IUCN, 2016; Nielsen et al., 2018). More broadly, hunting and illegal wildlife trade can invoke strong moral assessments of right and wrong citepfischer2013 and are under-represented issues in the economics and psychology literature (St John et al., 2011).

Three 'Control videos' were constructed, one for Bats, one for Lions, and one for Bats and Lions in the Savanna (henceforth 'Savanna'). Each of these videos had conservation-

[12]We were constrained in our choices, as many non-charismatic species had no or very dated information, and fewer still had comparable high-quality photos.

relevant information, such as the ecological role and conservation status of Bats and Lions. To construct treatment videos with additional audio-visual content on the anthropogenic cause of endangerment, each of the three control videos was augmented by one photo and an additional line of voice-over script stating threats from hunting and illegal wildlife trade (referred to as 'Cause videos'). Thus, there were six videos in total, namely Bats, Lions and Savanna Control videos and Bats, Lions and Savanna Cause videos. Following Gross and Levenson (1995), the average length of each video is 150 seconds, and each photo is displayed for around 6-10 seconds. Details of each video, alongside the hypothesis and experimental design, are discussed in the experimental design subsection.

But before proceeding, we make a note of some caveats. First, the conservation status of Lions and Bats is not identical, given the IUCN classifies lions as 'vulnerable' and bats as 'threatened'. Previous work finds the degree of endangerment status impacts willingness to pay for conservation. For instance, Tisdell et al. (2007) found that WTP for conservation and the level of species endangerment are positively correlated (also see Macdonald et al. (2015). Thus, any difference in donations between Lions and Bats across movies will also capture this difference in endangerment status, if subjects know and act on the difference.[13] Second, we treat species charisma as a black box composed of multiple constituent factors (such as size, taxonomy, popularity), in line with extant economics literature.[14] As phylogenetic differences may exert independent effects on behaviour, we attempt to control for some attributes, by picking mammals with forward facing eyes. Another feature typifying species charisma is fame and popularity. However, we try to control for prior informational differences by providing conservation-relevant information and hold constant the Savanna habitat in a standardised format across all videos. As we are primarily interested in the impact of media content via videos, disentangling the relative effects of each factor constituting charisma, is left for future work.[15]

[13]While 8 out of 12 subjects in the pilot study did not know the difference between threatened and vulnerable endangerment status, it is unclear whether the final sample knows the difference, as we did not collect this information.

[14]Metrick and Weitzman (1996) choose 'physical length of an average representative of the species' to identify charismatic species, with the only explanation that, 'we have not obtained a satisfactory measure of 'charisma', although we have received many creative suggestions' (pp. 4). Morse-Jones et al. (2012) do not define charisma, but their choice of charismatic species is 'relatively large and well-known mega-fauna such as the lion or gorilla, and non-charismatic as birds, reptiles, and amphibians.'

[15]Five common elements are physical and phylogenetic features (large mammals, with forward facing eyes), ecological features, cultural and symbolic value, affect and fame (Macdonald et al. (2015); Bowen-Jones and Entwistle (2002); Lorimer (2007) examine non-human charisma in more detail). Other work investgates how particular physical attributes like eyes, are particularly important; Manesi et al. (2015) observed that participants wished to donate to save spotted butterflies (with eye-like dots) and expressed more concern over them, compared to spotless butterflies.

2.3.3 Experimental design

Each subject was randomly assigned to watch one of the six videos. This design follows experimental methods previously employed in the literature to examine the impact of the audio-visual message content on behaviour and attitudes (e.g. in Greitemeyer (2013); van der Linden (2015). More precisely, Study 1 uses a between-subjects 'build on' or 3 x 3 fractional factorial experimental design to examine if donations are affected by the type of media content from differences across (i) Bats, Lions, Savanna Control videos, (ii) Bats, Lions, Savanna Cause videos and (iii) three Cause videos with the incentive of public recognition. Study 2 on affect uses a between-subjects 3 x 2 factorial design and crosses (i) Bats, Lions, Savanna Control videos and (ii) Bats, Lions, Savanna Cause videos to map changes in affective states from Bats, Lions and Savanna and to disentangle the outrage effect.[16]

Control videos: In the Bats and Lion Control videos, each species is introduced and located within the African Savanna, followed by conservation-relevant information about its ecological role and conservation status. In the Savanna video that locates both Bats and Lions within a natural habitat, the voice-over first introduces the habitat and states 'The diverse community of organisms that live here depend on each other to form a complex food web'. The first line emphasises that the habitat is a larger and more complex public good than a single species, and the second line emphasises that the habitat is one coherent unit, composed of interdependent parts. This introduction is followed by a sequence on the Bat and Lion, with their ecological role and conservation status, with the photos and script standardised so that it is similar to the previous single-species Control videos.

Cause videos: The Bats, Lions and Savanna Cause videos are identical to the Bats, Lions and Savanna Control videos respectively, barring a one-line voice-over in each video that states that the population of each species faces a threat from illegal hunting and poaching by humans, and contains one additional photo demonstrating illegal hunting. All other images and the script are indistinguishable from the Control videos.

Cause Videos + Public recognition: All subjects receiving this treatment are assigned to one of the three Cause videos. The only difference from the previous treatment group is an additional paragraph in the donation appeal page which states, "To publicly acknowledge your donation, 'The Beaver', which is the newspaper of the LSE Student Union will run a short piece listing the names of the donors and the charity later this

[16]We feel more comfortable with a between-subjects rather than within-subjects design because we are concerned that exposure to multiple videos will not yield clean treatment effects on donations or affect.

year. There will also be posters listing the names of the donors and the charity in the Saw Swee Hock Student Centre and the LSE Library. Please write your name in capital letters (e.g. FIRST-NAME LAST-NAME), on the form to be mentioned."

2.3.4 Hypotheses

We formulate three hypotheses to study the impact of media content of biodiversity conservation videos on pro-sociality and affect, based on the literature reviewed in the previous section. Drawing from studies such as Metrick and Weitzman (1998); Christie et al. (2006); Tisdell et al. (2007) and Lorimer (2007), we propose that media content about different species have a 'charismatic megafauna effect' because they can change both pro-social behaviours towards biodiversity conservation and experienced affective states in the following hypothesis:

Hypothesis I: Videos with charismatic species elicit higher charitable donations relative to videos with non-charismatic species in Study 1 (i.e., Donations after exposure to Bats control videos $<$ Donations after exposure to Lions control videos). Videos with charismatic species elicit higher positive affect, relative to videos with non-charismatic species in Study 2.

Next, following findings of the 'outrage effect' reported in Bulte et al. (2005) and Kahneman et al. (1993), we propose that media content anthropogenic cause of endangerment will also impact revealed pro-sociality and affect in the second hypothesis:

Hypothesis II: Videos with the anthropogenic cause of endangerment will elicit higher charitable donations in Study 1, i.e., Donations after exposure to Cause videos ¿ Donations after exposure to Control videos. Videos with the anthropogenic cause of endangerment will elicit higher negative affect (namely anger), relative to videos without audiovisual information on the anthropogenic cause of endangerment in Study 2.

Given that public visibility and social recognition can increase charitable giving in studies such as Ariely et al. (2009) and Karlan and McConnell (2014), we test the third and final hypothesis:

Hypothesis III: The offer of public recognition will increase charitable donations, i.e., Donations after exposure to Cause videos $<$ Donations after exposure to Cause videos + Public recognition.

Finally, we also consider if there are heterogeneous treatment effects, by examining the behavioural responses of 'pro-social' subjects, i.e., those who donated to charities outside the lab. On the one hand, it is likely that past donors may be more sensitive to the treatments, as they report having engaged in pro-social behaviour in the real world. Along these lines, there is evidence that pro-sociality in the lab predicts behaviour in the field (e.g. in Benz and Meier (2008)). Conversely, they may also be likely to donate less in a lab setting, because they already donate outside the lab. Other studies find no association or weak evidence on the congruence between giving in experimental games and in real life settings (Galizzi and Navarro-Martínez, 2018). Given this mixed evidence from previous work, we pay special attention to those who identify as 'Past donors' and their behaviour in the current setting.

2.3.5 Charitable donations

After subjects watched the video, they faced the charitable donations task. We adopted a modified dictator game used in other charitable giving experiments (Eckel and Grossman, 1996; Konow, 2010). Each subject could allocate any part of an endowment of £25 (in increments of £1), to the African Wildlife Foundation. The framing is standard in the literature, and all donations go to 'conserve vulnerable African species and their habitats' - not the species or habitat in the video clip. The donation page featured a photo of a single, forward facing Bat or Lion for the individual species videos. In the Savanna treatment, the same Bat and Lion photos were used, with one additional picture of the Savanna grassland. We adopted several design features to make the decision setting more realistic. We choose £25 as the endowment because it is a commonly suggested middle-level amount used by conservation charities. Subjects could receive a mailed receipt of their donation amount if they were selected for the pay-out and were asked to write down their lab identification code and postal address if they so desired. The offer of the receipt served the additional purpose of increasing trust in the experiment and the charity.

Some of our experimental design choices can affect the observed results. Engel (2011)'s meta-analysis of giving, in dictator games, finds that high stakes can dampen offers, and we may observe the same pattern in this experiment as the endowment in this experiment is five times the participation fee. On the other hand, it is possible that subjects are generous, because they have a windfall endowment (Carlsson et al., 2013).[17] Finally, as we use

[17] Moreover, all subjects were video-recorded throughout the experiment, which is likely to have increased donations if they 'felt' observed (Haley and Fessler, 2005). Every subject has to make the donation decision, i.e., we do not give subjects the chance to opt out of the donation task, which has been found to reduce sharing in lab and field settings (Andreoni et al., 2017; Lazear et al., 2012; DellaVigna et al., 2012).

a slider task, the default is set to £0 across all experimental interventions. All these design factors are constant across treatments groups, and we do not expect them to interact with the treatments themselves, but should be kept in mind while interpreting our results.

2.3.6 Affect

The affective states were selected from the PANAS-X affect schedule (Watson and Clark, 1999) and followed the elicitation procedure recommended in (Gross and Levenson, 1995) to measure experienced affect after watching videos. Subjects were asked to rate from a scale of 1 to 5 how much of each of the positive and negative affect they feel while watching the videos, namely, angry, sad, guilty, happy, calm and interest, that they felt while watching the videos. Previous research which links emotions to action tendencies supports our choices about affective states. For example, 'anger' has been associated with a tendency to restore justice or hold individuals responsible, and sadness with loss and the tendency to acquire new goods (Keltner and Lerner, 2010). 'Sympathy' has been associated with pro-sociality (e.g. Small et al. (2007). As clips of wildlife and natural landscapes are often used in experiments to elicit neutral affective states, we also included 'calm'.

Subjects answered the PANAS-X affect questions directly after watching the video clip, and we randomised the order of the list of affect types to mitigate order effects.[18] Most studies rely on self-reports using multi-item scales, which are confirmed and validated by equivalent results from fMRI studies (Harbaugh et al., 2007; Genevsky et al., 2013). However, we also included an implicit word association exercise, as an additional robustness check-in Study 2. After reporting affect, subjects were asked to list the first three words that come to mind, while thinking about the video. The words are then grouped into positive and negative affect types based on the PANAS-X schedule, other conservation-related themes as applicable.

2.3.7 Individual-level control variables

Given the large pool of student and non-student subjects, we expected some heterogeneity in behaviour and motivation. We asked if subjects had previously donated to any environmental and non-environmental charities, and about their membership status to the same. Three questions were posed to measure pro-environmental behaviour, namely how often individuals bought (a) eco-friendly products (b) organic, local and seasonally

[18]In study 1, subjects were also asked questions on affect about the video clip, after making their donation decision. However, we prefer to disregard these responses in the analysis, as that donation decision can independently impact self-reports of affect.

grown food, and (c) if they recycled. Each item is rated on a 5-point Likert scale from 'Never' to 'Always', and scores of these three questions are averaged to form an average pro-environmental behaviour score. Lab experiments using dictator games find that women, non-students, and older participants make higher offers (Engel, 2011). Therefore, the experiment concludes with questions on socio-demographic attributes on age, gender and job status. We included filler questions to mitigate experimenter demand effects and randomised the order of all questions to reduce any order effects.[19]

2.3.8 Summary statistics for the pooled sample

The average age was 24.4 years (median age of 22 years), and 66.35% of the sample was female. Around 81% of the subjects were full-time students, and 76% of the sample reported that they had donated to a charity in the past.[20]. The average sample size for each treatment group was 42 in Study 1 and 36 in Study 2. Tables B.1 and B.2 present the individual-level characteristics for the pooled sample from both Study 1 and 2, and by intervention group respectively.

2.4 Study 1 results

2.4.1 Media content on donations

The average donation is £8.51 or 34.04% of the endowment. This figure is close to offers in charitable giving experiments, such as 30% in Eckel and Grossman (1996), but higher than offers in anonymous dictator games (around 20% in Camerer (2003). The median donation at £5 was made by 28.91% of subjects, and 20.42% of the sample donated £10. While 6.63% of the sample donated their entire endowment of £25, 14.59% gave nothing.[21]

Figure 2.1 illustrates the average donations by treatment group (with error bars of 95% confidence interval). Three empirical tendencies emerge: first, average contributions elicited after exposure to the Lions 'Control' video (£9.46) was higher than the Bats (£7.25), and Savanna control videos (£6.32). Secondly, for each type of video (i.e. across

[19]We also ask subjects willingness to pay for a green tax immediately after the affect questions, which we do not report in the current paper but discuss in greater detail in Chapter 3.

[20]This proportion is close to but marginally higher than, nationally representative U.K. survey estimates, where 67% reported making donations to a charity in 2015 (CAF, 2016)

[21]Figure B.1 shows the distribution of donations for the pooled sample. Skewness and kurtosis tests and Shapiro-Wilk tests for normality rejects that donations are normally distributed (both for the pooled sample and by treatment group).

Bats, Lions, and Savanna), additional media content on the anthropogenic cause of endangerment elicited higher average donations, compared to the control group videos. Thirdly, the Cause videos + Public recognition intervention evokes marginally lower average contributions than Bats and Savanna Cause videos (£7.10 and £7.89 for Bats and Savanna respectively). Probing further into the data, we see that fewer subjects choose not to donate when exposed to Lions videos, and this is illustrated in Figure 2.2 which displays the share of subjects choosing to donate an amount over £0 in the donation task by intervention group. On average, around 80% of subjects exposed to any of the Lion videos decided to donate, compared to 63.64% and 56.31% of the subjects shown any Bats or Savanna videos. Thus, the descriptive data provides tentative evidence for the charisma and outrage effect, but the impact of public recognition on donations is unclear.

[Figures 2.1 and 2.2]

Table 2.1 presents results from the regression models on donations. The outcome variable is the donation, and the two primary explanatory variables of interest are the treatment dummies on the type of media content. The first treatment dummy called the 'Species' variable has three categories of Bats, Lions or Savanna. The second treatment dummy called 'Cause' also has three categories for the Control video, Cause video or Cause video + Public recognition. We present results from both Tobit (Tobin, 1958) and Cragg-Hurdle regression models (Cragg, 1971), following econometric approaches used in previous dictator game experiments (Engel, 2011). As the upper boundary is the donation limit £25, models (1) and (2) present the Tobit regression models right-censored at £25. However, the donation choice can be conceptualised as a two-stage decision process instead: first, the probability of donating any non-zero amount, versus donating nothing; and second, the decision of how much to donate conditional of having decided to donate. In this case, we treat the lower boundary as 'observed' rather than censored, i.e., the probability of donating is treated as another observed behaviour (Wooldridge, 2010; Cragg, 1971). The specific advantage of this approach was that it allowed us to estimate if the treatments had separate impacts on both the probability of donating (Probability) and the amount donated conditional of having to donate (Amount).[22]

Thus, Models (3) to (10) in Table 2.1 present results from the Cragg-Hurdle models, such that 'Probability' reports coefficients from a Probit regression model and 'Amount' reports coefficients from a Truncated-linear regression model. The higher proportion of subjects choosing to donate when exposed to Lions videos suggests the Cragg-Hurdle model is appropriate. We use robust standard errors clustered at the subject-level for all

[22]Appendix B has a note on the Cragg-Hurdle model and estimation strategy used in the paper.

regression models, and the omitted category is the Bats control video. To control for potential session-level factors, we added session dummies, and an additional control variable for the number of subjects who attended each session, to control for the variation in the probability of the payoff from the charitable giving game. Individual controls included a dummy for whether the subject donated in the past (Past donor) and covariates on Pro-environmental behaviour, Age, Gender, Job status (Table B.3 presents the results of the full model).

[Table 2.1]

First, consider results from the Tobit regression models. From model (1) in Table 2.1, the coefficient on Lions is positive and significant at 5%, suggesting that the predicted value of donations is £1.7 higher for subjects in the Lions group compared to those in the Bats group, holding all other covariates constant. The coefficient remains stable when we add individual controls in model (2). The coefficient on Cause is also positive and significant at 5%, suggesting that for those exposed to information on the anthropogenic cause of treat, their predicted donation was higher by around £2 compared to those who were exposed to the control group videos. Note that the coefficient on Cause + Public recognition is positive, but not statistically significant.

Now we turn to the results of the Cragg-Hurdle regression models (models (3) to (10), Table 2.1). The positive coefficient on Lions in models (3) and (5) suggest that subjects are more likely to donate when exposed to Lions videos, compared to Bats (the difference is significant at 5%). While there is a positive coefficient on the amount donated by subjects, conditional on having decided to contribute, i.e., once they had cleared the hurdle (model (4) and (6)), it is not significant. Conversely, the treatment variable on Cause is positive and significant at 5% on the amount donated, conditional on having decided to donate. The predicted conditional mean estimates of donations or the predicted average marginal effect on contributions from the Cragg-Hurdle models are nearly identical to results from the Tobit models. For instance, in model (4), the average effect of watching Lion videos relative to Bats, holding other covariates constant is an increase in average donations by £1.53 (significant at 5%). Similarly, the average marginal effect of exposure to the Cause videos compared to the Control videos amounts to an increase in average donations by £2.01 (significant at 5%). This amount is comparable to the suggested online donation amounts for animal charities, which start from £2 per month. Note that the coefficient on Cause + Public recognition is negative in models (3) and (5), suggesting that the offer of public recognition reduces the likelihood of donating, but this difference is not statistically significant. The coefficient is however positive when considering the amount donated in models (4) and (6), but is again not statistically significant.

To summarise, our first set of results find there is a positive charisma effect on charitable donations. This result is consistent with previous findings that charismatic species elicit higher contributions, as in Thomas-Walters and J Raihani (2017) and other stated preference studies. However, our results extend the literature to show that the probability of donating is affected, rather than the amount, i.e., videos with charismatic species (Lions), increases the probability of making a charitable donation, relative to those with non-charismatic species (Bats), holding other variables constant. Secondly, audio-visual content on the anthropogenic source of conservation threat increases the charitable donation amount, conditional on having decided to donate, providing empirical support for the positive outrage effect on charitable donations, but we find no impact on the probability of donating. The positive relationship between information on the human-made cause of endangerment and donations is also consistent with previous work, such as (Bulte et al., 2005).

2.4.2 Pro-social subjects (Past donors)

We now restrict the sample to pro-social subjects, i.e., those who reported making donations to charities outside the lab (past donors) and use Cragg-Hurdle model to examine potential treatment effects. Models (7) to (10) in Table 2.1 show the results. Three important differences emerge. First, the coefficient on Lions is positive, but weakly significant, in models (7) and (9) (Probability, with and without individual controls). Second, the coefficient on Cause in the truncated linear regressions remains positive but increases in both economic and statistical significance (to the 1% significance level). For past donors, the average marginal effect of exposure to Control videos is £3.18, compared to the control group videos (significant at 1%).

Third, for donors, the treatment effect of the Cause + Public Recognition increases the amount donated in a statistically significant way (at the 5% level, models (4) and (6), relative to the Control videos). The average marginal effect is also economically meaningful: subjects exposed to videos with the anthropogenic cause of endangerment and the offer of public recognition, have higher donations amounts of £2.16, conditional of having decided to donate, compared to subjects who were exposed to videos with the cause of endangerment. This gives us the following result: Pro-social subjects (past donors) show a positive effect of Cause + Public recognition, i.e., the offer of public recognition increases the charitable donation amount, conditional on having decided to donate, relative to the control, videos.

2.4.3 Public recognition incentive on donations

Models (7) to (10) in Table 2.1 show an increase in donations for pro-social subjects exposed to Cause videos + Public recognition (relative to control videos), but the increase is of lower magnitude than being exposed to Cause videos without Public recognition. To obtain the separate treatment effect of the Public recognition incentive, we restrict the sample to those subjects exposed to either the Cause video (omitted category) or Cause + Public recognition (treatment dummy).

Table 2.2 reports the results of the Tobit and Cragg-Hurdle models. The coefficient on Public recognition is negative in all models, and weakly significant (at 10%) in (Tobit) model (2) when individual controls are added. The Probability of donating in model (3) is also faintly significant at 10% (translating into an average negative effect of £1.5). When we consider pro-social subjects (models (7) to (10)), the coefficient stays negative, but the difference is not statistically significant. This negative relationship is suggestive of the crowding-out effect of weak incentives on pro-social behaviour. While it is difficult to conclude why this is the case from the data available it is likely that the incentive is too weak to have a substantial positive effect on behaviour. Instead, it could have reminded subjects about what personal benefit they could derive from the donation or may have signalled to players that those who donate do so for self-interested motivations, i.e., to 'look good' rather than actually 'be good' (Gneezy and Rustichini, 2000; Bowles, 2008; Bowles and Polania-Reyes, 2012).[23]

[Table 2.2]

2.4.4 Limitations and robustness

Our results are robust to the addition of session and individual controls, which yield coefficients of comparable economic magnitude. For instance, a one-unit increase in the average pro-environmental behaviour score was associated with an increase in predicted donations by around £1.70 (Table B.3 in Appendix B). We also checked for heterogeneous treatment effects by crossing the dummy on past donor with the treatment dummies on video content about Cause to find qualitatively similar results in the restricted sub-sample models. We also interacted the dummies on the types of video, i.e. Bats/Lions/Savanna,

[23]There is some support for the possibility that the incentive is weak, as only 17.6% subjects exposed to the Cause videos + Public recognition treatment opted to have their name mentioned on the receipts.

with control videos/Cause/Cause + Public recognition dummies. Lions positively predict the likelihood of donating at 10% in the full sample, and the Cause variable positively predicts the amount donated in the restricted sample of past donors. We also replicated our analysis using other specifications, to find qualitatively similar results (such as Ordinary Least Squares, Logistic regression models). These results are omitted for brevity, but available on request.[24]

We then considered the possibility that subjects may choose not to donate £0 because they mistrust the experiment or charity. If subjects decided to give £0, they were asked to state their top two reasons for choosing not to donate after they completed affect questions. 'Rather keep the money' was the top reason chosen (25.5% and 27.3% of non-donors chose this as reason one and reason two respectively). 'Do not trust the charity' was chosen by 18.2% of the non-donors (10 subjects) and came in as the third most popular reason (and was also chosen by four subjects as reason 2). Overall only four subjects chose 'Do not trust the experiment' suggesting that the research design was successful in convincing subjects that the donations would indeed go to the charity.[25] We restricted the sample by dropping the 17 observations of the non-donors that stated that they did not trust either the charity or the experiment as one of the reasons for not donating. The estimated treatment effects are qualitatively similar and are available on request. Finally, we cannot fully control for the context subjects bring with them into the lab or the numerous differences that exist between the lab and field setting, which threaten external validity. Instead, we attempt to estimate the impact of these factors on our results, through the collection of observable subject attributes and past donations behaviour.

2.5 Study 2 results

2.5.1 Media content on Experienced Affect

We now turn to the impact of the biodiversity conservation videos on self-reported affect. Figures 2.3 to 2.9 illustrate the average scores of experienced affective states (angry, sad, guilty, sympathy, happy, calm and interest), for subjects exposed to the control group videos and videos with additional content on the anthropogenic cause of endangerment. Results from ordinal logistic regression models are presented in Table 2.3 (with standard

[24]We follow Humphreys (2010) and Wooldridge (2010) to treat the boundary value of £0 donations as observed, rather than a sample selection problem with no missing data, so we do not use a Heckman selection model.

[25]For more detail, please refer to Figure B.2 Appendix B.

errors clustered at the subject level, with session dummies and individual controls).

Several findings emerge. First, we consider the effects of species habitat videos. Exposure to Lions videos elicited higher scores of experienced happiness (significant at 5%, model (5) in Table 2.3). This result implies an increase in the odds of reporting the highest happiness scores by 2.42 times, holding other variables constant, relative to the Bats Control videos. The increase in self-reported affect is in line with previous studies that link species charisma to positive affect and likeability (Lorimer, 2007; Tisdell et al., 2007; Brambilla et al., 2013; Martín-López et al., 2007). Exposure to Savanna videos, on the other hand, elicited higher reported interest, where the odds of reporting highest Interest scores were also around 2.16 times higher, relative to Bats videos. There was also a positive effect on experienced calm (significant at 10%).

Secondly, there was an increase in the intensity of most types of affect between subjects exposed to Control and Cause videos. Cause videos increase the intensity of anger, and interest (significant at 1%), and sadness and sympathy (at 5%). From model (1) in Table 2.3, the odds of highest angry affect score versus the low categories were 2.85 times higher, for 'Cause videos, when holding other variables constant. The odds of reported sadness at the highest score are were 1.84 times higher for Cause videos compared to control group videos. Model (4) considers sympathy, where the odds of subjects reporting the highest sympathy and interest scores are 1.70 and 2.10 times higher for Cause videos, respectively. This finding is consistent with the outrage effect, as well as other studies linking sadness and sympathy to giving (Kahneman et al., 1993; Kahneman and Knetsch, 1992; Small et al., 2007). But cause videos also elicited weakly higher reported happiness (at 10%). While it is unclear why this may be the case, one explanation could be that individuals experience greater emotional arousal across all types of affective when the human-made cause of harm is made salient or when they experience greater 'outrage'. However, further investigation is needed to examine this idea.

[Table 2.3]

[Figures 2.3 to 2.9]

In summary, audio-visual media content about different species and habitats, elicit different affective responses: videos with charismatic species (Lions), increases self-reported happiness, and those with composite habitats (Savanna) evoke greater interest, relative to videos with non-charismatic species (Bats). Finally, media content on the anthropogenic cause of threat in conservation videos causes an increase a range of self-reported affect types, including anger, sadness, sympathy, happiness and interest. This extends previous experimental evidence in Kahneman et al. (1993), who measure an increase in one type of negative affect, as subjects report feeling more 'upset'. More broadly, these results are in line with studies that find individuals experience mixed emotional states, which are separable by experience, and linked to the narratives told by charitable organizations (Ruth et al., 2002; Kemp et al., 2012; Merchant et al., 2010; Bennett, 2015). From an alternate theoretical perspective, citetkonow2009 also found that dictators experienced more of a 'good mood' when the recipients are charities, and 'bad mood' when they are fellow students, highlighting that the target recipient (and perceived need) can also influence the donor's experienced affect.

2.5.2 Limitations and Robustness

Our results are robust to the addition of session fixed effects and individual controls. Notably, when we look at the individual's attributes, pro-environmental behaviour scores are significantly and positively related to anger, sadness, and interest (at 1% significance level), and sympathy (at 5%). We also replicate the analysis with the interaction between treatment dummies on the types of video (i.e. Bats/Lions/Savanna) with Control videos/Cause dummies, with qualitatively similar results. Finally, we consider results of the implicit word association test, to examine the frequency of positive and negative affect words across different treatments. We find that Lions elicit a higher count of positive affect words (mainly related to happiness/joviality), and this is congruent with our experimental results on self-reported affect (Table B.5 in Appendix B). That said, it is beyond the scope of the both studies to unpack the causal effect of different types of affect or the intensity of experienced affect on donations behaviour.

2.6 Discussion and conclusion

The ongoing sixth mass extinction event mandates urgent public attention and support for conservation work. There is a dearth of empirical evidence about what motivates people to give to conservation and how to design effective interventions to this end. This paper aims to fill the gap by exploring how different types of audiovisual media content impacts charitable donations and experienced affect, by using a series of lab experiments. The novelty of this effort is to disentangle the behavioural and emotional basis of the charismatic megafauna effect and outrage effect. We attempt this task by exposing individuals to brief biodiversity conservation videos with narrative content about charismatic Lions, non-charismatic Bats and a complex Savanna habitat composed of both species, both with and without the anthropogenic cause of endangerment. We also examine if a non-pecuniary incentive of public recognition impacts charitable donations. In this way, we attempt to push the frontier of existing evidence of how resources are allocated towards biodiversity by considering a new context and potential psychological processes that can underpin decision-making therein.

The results from both Study 1 and 2 yield evidence for the charismatic megafauna and outrage effect, but extend the previous literature by isolating distinct channels of behavioural impact. Specifically, videos with charismatic Lions increased the likelihood of donating, but not the amount donated. Conversely, videos with the human cause of endangerment, increased the amount donated conditional on having decided to donate, but not the likelihood of donating. We also noted that treatment effects are heterogeneous: the offer of public recognition increased donations for past donors or those who have selected into altruistic giving environments outside the lab, albeit to a lower extent than exposure to Cause videos, with no incentive. Effects were sizeable and ranged from £1.5 to £3. To put this into perspective, £2 is the suggested lower limit on donations on many conservation charity websites. Study 2 reveals videos elicit complex and mixed emotional reactions in subjects: for instance, videos with the anthropogenic cause of threat caused an increase in self-reported anger, sadness and interest, and charismatic Lions increased self-reported happiness.

Our results hold some potential implications for those in academia, conservation, and policy. One implication is that conservation organisations could diversify the type of species used in video appeals by featuring more non-charismatic species and complex habitats, and by making explicit the anthropogenic cause of species endangerment. They could continue to use charismatic species to widen their donor base as a complementary strategy. This approach simultaneously addresses previously voiced concerns about the marginalisation of non-charismatic species and ignorance of the anthropogenic drivers of the mass extinction event. It also capitalises on the benefits of using charismatic species. Replicating these results in different contexts and samples, and by using different narratives, alongside field testing is an exciting prospect for future research to ensure a robust evidence base for policy.

Finally, we suggest that mixed emotional reactions can have short-term effects on prosociality towards biodiversity if subjects see 'red' but act 'green'. While we cannot shed light on the causal effects of emotions on donations, this is another promising avenue for future work. Using alternative bio-physical measures of affect like fMRI scanning or skin conductance technologies may be particularly fruitful methods to uncover these causal relationships.

Bibliography

Andreoni, J. (1989). Giving with impure altruism: Applications to charity and ricardian equivalence. *Journal of political Economy*, 97(6):1447–1458.

Andreoni, J. (1990). Impure altruism and donations to public goods: A theory of warm-glow giving? *Economic Journal*, 100(401):464–77.

Andreoni, J., Rao, J. M., and Trachtman, H. (2017). Avoiding the ask: A field experiment on altruism, empathy, and charitable giving. *Journal of Political Economy*, 125(3):625–653.

Ariely, D., Bracha, A., and Meier, S. (2009). Doing good or doing well? image motivation and monetary incentives in behaving prosocially. *American Economic Review*, 99(1):544–55.

Ashraf, N., Camerer, C. F., and Loewenstein, G. (2005). Adam smith, behavioral economist. *Journal of Economic Perspectives*, 19(3):131–145.

Ballantyne, R., Packer, J., Hughes, K., and Dierking, L. (2007). Conservation learning in wildlife tourism settings: Lessons from research in zoos and aquariums. *Environmental Education Research*, 13(3):367–383.

Bauer, H., Chapron, G., Nowell, K., Henschel, P., Funston, P., Hunter, L. T., Macdonald, D. W., and Packer, C. (2015). Lion (panthera leo) populations are declining rapidly across africa, except in intensively managed areas. *Proceedings of the National Academy of Sciences*, 112(48):14894–14899.

Bénabou, R. and Tirole, J. (2006). Incentives and prosocial behavior. *American economic review*, 96(5):1652–1678.

Bénabou, R. and Tirole, J. (2011). Identity, morals, and taboos: Beliefs as assets. *The Quarterly Journal of Economics*, 126(2):805–855.

Bennett, R. (2015). Individual characteristics and the arousal of mixed emotions: Consequences for the effectiveness of charity fundraising advertisements. *International Journal of Nonprofit and Voluntary Sector Marketing*, 20(2):188–209.

Benz, M. and Meier, S. (2008). Do people behave in experiments as in the field?—evidence from donations. *Experimental economics*, 11(3):268–281.

Bowen-Jones, E. and Entwistle, A. (2002). Identifying appropriate flagship species: the importance of culture and local contexts. *Oryx*, 36(2):189–195.

Bowles, S. (2008). Policies designed for self-interested citizens may undermine" the moral sentiments": Evidence from economic experiments. *science*, 320(5883):1605–1609.

Bowles, S. and Polania-Reyes, S. (2012). Economic incentives and social preferences: substitutes or complements? *Journal of Economic Literature*, 50(2):368–425.

Brambilla, M., Gustin, M., and Celada, C. (2013). Species appeal predicts conservation status. *Biological conservation*, 160:209–213.

Brown, G. M. and Shogren, J. F. (1998). Economics of the endangered species act. *Journal of Economic Perspectives*, 12(3):3–20.

Brown, T. C., Nannini, D., Gorter, R. B., Bell, P. A., and Peterson, G. L. (2002). Judged seriousness of environmental losses: reliability and cause of loss. *Ecological Economics*, 42(3):479–491.

Bulte, E., Gerking, S., List, J. A., and De Zeeuw, A. (2005). The effect of varying the causes of environmental problems on stated wtp values: evidence from a field study. *Journal of Environmental Economics and Management*, 49(2):330–342.

Bulte, E. H. and Van Kooten, G. C. (1999). Marginal valuation of charismatic species: implications for conservation. *Environmental and Resource Economics*, 14(1):119–130.

Butchart, S. H., Walpole, M., Collen, B., Van Strien, A., Scharlemann, J. P., Almond, R. E., Baillie, J. E., Bomhard, B., Brown, C., Bruno, J., et al. (2010). Global biodiversity: indicators of recent declines. *Science*, page 1187512.

CAF (2016). Caf u.k. giving 2015. https://www.cafonline.org/docs/default-source/personal-giving/caf_ukgiving2015_1891a_web_230516.pdf?sfvrsn=2 [Accessed: October 31 2017].

Camerer, C., Loewenstein, G., and Prelec, D. (2005). Neuroeconomics: How neuroscience can inform economics. *Journal of economic Literature*, 43(1):9–64.

Camerer, C. F. (2003). *Behavioral game theory: Experiments in strategic interaction*. Princeton University Press.

Cardenas, J. C., Stranlund, J., and Willis, C. (2000). Local environmental control and institutional crowding-out. *World development*, 28(10):1719–1733.

Carlsson, F., He, H., and Martinsson, P. (2013). Easy come, easy go. *Experimental Economics*, 16(2):190–207.

Caro, T. and Riggio, J. (2013). The big 5 and conservation. *Animal Conservation*, 16(3):261–262.

Carson, R. T. (2012). Contingent valuation: A practical alternative when prices aren't available. *Journal of Economic Perspectives*, 26(4):27–42.

Ceballos, G., Ehrlich, P. R., Barnosky, A. D., García, A., Pringle, R. M., and Palmer, T. M. (2015). Accelerated modern human–induced species losses: Entering the sixth mass extinction. *Science advances*, 1(5):e1400253.

Ceballos, G., Ehrlich, P. R., and Dirzo, R. (2017). Biological annihilation via the ongoing sixth mass extinction signaled by vertebrate population losses and declines. *Proceedings of the National Academy of Sciences*, 114(30):E6089–E6096.

Christie, M., Hanley, N., Warren, J., Murphy, K., Wright, R., and Hyde, T. (2006). Valuing the diversity of biodiversity. *Ecological economics*, 58(2):304–317.

Clucas, B., McHugh, K., and Caro, T. (2008). Flagship species on covers of us conservation and nature magazines. *Biodiversity and Conservation*, 17(6):1517.

Cornelius, R. R. (1996). *The science of emotion: Research and tradition in the psychology of emotions.* Prentice-Hall, Inc.

Cotterill, S., John, P., and Richardson, L. (2013). The impact of a pledge request and the promise of publicity: a randomized controlled trial of charitable donations. *Social Science Quarterly*, 94(1):200–216.

Cragg, J. G. (1971). Some statistical models for limited dependent variables with application to the demand for durable goods. *Econometrica: Journal of the Econometric Society*, pages 829–844.

Dana, J., Cain, D. M., and Dawes, R. M. (2006). What you don't know won't hurt me: Costly (but quiet) exit in dictator games. *Organizational Behavior and human decision Processes*, 100(2):193–201.

Dana, J., Weber, R. A., and Kuang, J. X. (2007). Exploiting moral wiggle room: experiments demonstrating an illusory preference for fairness. *Economic Theory*, 33(1):67–80.

Dawson, D. and Shogren, J. F. (2001). An update on priorities and expenditures under the endangered species act. *Land Economics*, 77(4):527–532.

DellaVigna, S., List, J. A., and Malmendier, U. (2012). Testing for altruism and social pressure in charitable giving. *The quarterly journal of economics*, 127(1):1–56.

Desvousges, W. H., Reed Johnson, F., Dunford, R. W., Wilson, N. K., and Boyle, K. J. (1993). Measuring natural resource damages with contingent valuation. In *Contingent valuation: A critical assessment*, pages 91–164. Emerald Group Publishing Limited.

Dirzo, R., Young, H. S., Galetti, M., Ceballos, G., Isaac, N. J., and Collen, B. (2014). Defaunation in the anthropocene. *science*, 345(6195):401–406.

Douglas, L. R. and Winkel, G. (2014). The flipside of the flagship. *Biodiversity and conservation*, 23(4):979–997.

Eckel, C. C. and Grossman, P. J. (1996). Altruism in anonymous dictator games. *Games and economic behavior*, 16(2):181–191.

Engel, C. (2011). Dictator games: A meta study. *Experimental Economics*, 14(4):583–610.

Falk, J. H. and Balling, J. D. (2010). Evolutionary influence on human landscape preference. *Environment and Behavior*, 42(4):479–493.

Fleming, P. A. and Bateman, P. W. (2016). The good, the bad, and the ugly: which australian terrestrial mammal species attract most research? *Mammal Review*, 46(4):241–254.

Galizzi, M. M. and Navarro-Martínez, D. (2018). On the external validity of social preference games: a systematic lab-field study. *Management Science*.

Gavin, N. T. and Marshall, T. (2011). Mediated climate change in britain: Scepticism on the web and on television around copenhagen. *Global Environmental Change*, 21(3):1035–1044.

Genevsky, A., Västfjäll, D., Slovic, P., and Knutson, B. (2013). Neural underpinnings of the identifiable victim effect: Affect shifts preferences for giving. *Journal of Neuroscience*, 33(43):17188–17196.

Gneezy, U. and Rustichini, A. (2000). Pay enough or don't pay at all. *The Quarterly Journal of Economics*, 115(3):791–810.

Greitemeyer, T. (2013). Beware of climate change skeptic films. *Journal of environmental Psychology*, 35:105–109.

Gross, J. J. and Levenson, R. W. (1995). Emotion elicitation using films. *Cognition & emotion*, 9(1):87–108.

Haley, K. J. and Fessler, D. M. (2005). Nobody's watching?: Subtle cues affect generosity in an anonymous economic game. *Evolution and Human behavior*, 26(3):245–256.

Han, K.-T. (2007). Responses to six major terrestrial biomes in terms of scenic beauty, preference, and restorativeness. *Environment and Behavior*, 39(4):529–556.

Hanley, N., Boyce, C., Czajkowski, M., Tucker, S., Noussair, C., and Townsend, M. (2017). Sad or happy? the effects of emotions on stated preferences for environmental goods. *Environmental and Resource Economics*, 68(4):821–846.

Harbaugh, W. T. (1998). The prestige motive for making charitable transfers. *The American Economic Review*, 88(2):277–282.

Harbaugh, W. T., Mayr, U., and Burghart, D. R. (2007). Neural responses to taxation and voluntary giving reveal motives for charitable donations. *Science*, 316(5831):1622–1625.

Helm, D. and Hepburn, C. (2012). The economic analysis of biodiversity: an assessment. *Oxford Review of Economic Policy*, 28(1):1–21.

Herzog, H. A. and Burghardt, G. M. (2005). The next frontier: Moral heuristics and the treatment of animals. *Behavioral and Brain Sciences*, 28(4):554–555.

Hsee, C. K. and Rottenstreich, Y. (2004). Music, pandas, and muggers: on the affective psychology of value. *Journal of Experimental Psychology: General*, 133(1):23.

Hughes-Games, M. (2017). The bbc's planet earth ii did not help the natural world. https://www.theguardian.com/commentisfree/2017/jan/01/bbc-planet-earth-not-help-natural-world [Accessed: 28 March 2018].

Humphreys, B. R. (2010). Dealing with zeros in economic data. https://www.researchgate.net/profile/Brad_Humphreys/publication/265222409_Dealing_With_Zeros_in_Economic_Data/links/559bf7c208ae898ed650b296.pdf [Accessed: 31 October 2017].

Irlenbusch, B. and Ruchala, G. K. (2008). Relative rewards within team-based compensation. *Labour economics*, 15(2):141–167.

IUCN (2016). Red list of threatened species. http://www.iucnredlist.org/photos/2016 [Accessed: October 2016].

Jacobs, M. H. (2009). Why do we like or dislike animals? *Human Dimensions of Wildlife*, 14(1):1–11.

Jacobsen, J. B., Boiesen, J. H., Thorsen, B. J., and Strange, N. (2008). What's in a name? the use of quantitative measures versus 'iconised'species when valuing biodiversity. *Environmental and resource economics*, 39(3):247–263.

Jenni, K. and Loewenstein, G. (1997). Explaining the identifiable victim effect. *Journal of Risk and Uncertainty*, 14(3):235–257.

Kahn Jr, P. H., Saunders, C. D., Severson, R. L., Myers Jr, O. E., and Gill, B. T. (2008). Moral and fearful affiliations with the animal world: Children's conceptions of bats. *Anthrozoös*, 21(4):375–386.

Kahneman, D. (2003). Maps of bounded rationality: Psychology for behavioral economics. *American economic review*, 93(5):1449–1475.

Kahneman, D. and Frederick, S. (2002). Representativeness revisited: Attribute substitution in intuitive judgment. *Heuristics and biases: The psychology of intuitive judgment*, 49:81.

Kahneman, D. and Knetsch, J. L. (1992). Valuing public goods: the purchase of moral satisfaction. *Journal of environmental economics and management*, 22(1):57–70.

Kahneman, D. and Ritov, I. (1994). Determinants of stated willingness to pay for public goods: A study in the headline method. *Journal of Risk and Uncertainty*, 9(1):5–37.

Kahneman, D., Ritov, I., Jacowitz, K. E., and Grant, P. (1993). Stated willingness to pay for public goods: A psychological perspective. *Psychological science*, 4(5):310–315.

Kahneman, D., Schkade, D., and Sunstein, C. (1998). Shared outrage and erratic awards: The psychology of punitive damages. *Journal of Risk and Uncertainty*, 16(1):49–86.

Karlan, D. and McConnell, M. A. (2014). Hey look at me: The effect of giving circles on giving. *Journal of Economic Behavior & Organization*, 106:402–412.

Kellert, S. R. and Wilson, E. O. (1995). *The biophilia hypothesis*. Island Press.

Keltner, D. and Lerner, J. S. (2010). Emotion. In Fiske, S. T., Gilbert, D. T., and Lindzey, G., editors, *Handbook of social psychology*, pages 317–352. John Wiley and Sons Inc.

Kemp, E., Bui, M., and Chapa, S. (2012). The role of advertising in consumer emotion management. *International Journal of Advertising*, 31(2):339–353.

Kingston, T. (2016). Cute, creepy, or crispy—how values, attitudes, and norms shape human behavior toward bats. In *Bats in the Anthropocene: Conservation of Bats in a Changing World*, pages 571–595. Springer.

Knight, A. J. (2008). "bats, snakes and spiders, oh my!" how aesthetic and negativistic attitudes, and other concepts predict support for species protection. *Journal of Environmental Psychology*, 28(1):94–103.

Konow, J. (2010). Mixed feelings: Theories of and evidence on giving. *Journal of Public Economics*, 94(3-4):279–297.

Kontoleon, A. and Swanson, T. (2003). The willingness to pay for property rights for the giant panda: can a charismatic species be an instrument for nature conservation? *Land Economics*, 79(4):483–499.

La Ferrara, E. (2016). Mass media and social change: Can we use television to fight poverty? *Journal of the European Economic Association*, 14(4):791–827.

Lacetera, N. and Macis, M. (2010). Social image concerns and prosocial behavior: Field evidence from a nonlinear incentive scheme. *Journal of Economic Behavior & Organization*, 76(2):225–237.

Lazear, E. P., Malmendier, U., and Weber, R. A. (2012). Sorting in experiments with application to social preferences. *American Economic Journal: Applied Economics*, 4(1):136–63.

Leader-Williams, N. and Dublin, H. T. (2000). Charismatic megafauna as flagship species. *Conservation Biology Series- Cambridge*, pages 53–84.

Lindenmayer, D., Manning, A., Smith, P., Possingham, H. P., Fischer, J., Oliver, I., and McCarthy, M. (2002). The focal-species approach and landscape restoration: a critique. *Conservation biology*, 16(2):338–345.

Loewenstein, G. (2000). Emotions in economic theory and economic behavior. *American economic review*, 90(2):426–432.

Loomis, J. B. and White, D. S. (1996). Economic benefits of rare and endangered species: summary and meta-analysis. *Ecological Economics*, 18(3):197–206.

Lorimer, J. (2007). Nonhuman charisma. *Environment and Planning D: Society and Space*, 25(5):911–932.

Lundhede, T. H., Jacobsen, J. B., Hanley, N., Fjeldså, J., Rahbek, C., Strange, N., and Thorsen, B. J. (2014). Public support for conserving bird species runs counter to climate change impacts on their distributions. *PloS one*, 9(7):e101281.

Macdonald, E., Burnham, D., Hinks, A., Dickman, A., Malhi, Y., and Macdonald, D. (2015). Conservation inequality and the charismatic cat: Felis felicis. *Global Ecology and Conservation*, 3:851–866.

MacKerron, G. and Mourato, S. (2013). Happiness is greater in natural environments. *Global Environmental Change*, 23(5):992–1000.

Mainwaring, L. (2001). Biodiversity, biocomplexity, and the economics of genetic dissimilarity. *Land Economics*, 77(1):79–83.

Manesi, Z., Van Lange, P. A., and Pollet, T. V. (2015). Butterfly eyespots: Their potential influence on aesthetic preferences and conservation attitudes. *PloS one*, 10(11):e0141433.

Marešová, J. and Frynta, D. (2008). Noah's ark is full of common species attractive to humans: The case of boid snakes in zoos. *Ecological Economics*, 64(3):554–558.

Markowitz, E. M., Slovic, P., Västfjäll, D., and Hodges, S. D. (2013). Compassion fade and the challenge of environmental conservation. *Judgment and Decision Making*, 8(4):397.

Martín-López, B., Montes, C., and Benayas, J. (2007). The non-economic motives behind the willingness to pay for biodiversity conservation. *Biological conservation*, 139(1-2):67–82.

McCarthy, D. P., Donald, P. F., Scharlemann, J. P., Buchanan, G. M., Balmford, A., Green, J. M., Bennun, L. A., Burgess, N. D., Fishpool, L. D., Garnett, S. T., et al. (2012). Financial costs of meeting global biodiversity conservation targets: current spending and unmet needs. *Science*, page 1229803.

Merchant, A., Ford, J. B., and Sargeant, A. (2010). Charitable organizations' storytelling influence on donors' emotions and intentions. *Journal of Business Research*, 63(7):754–762.

Metrick, A. and Weitzman, M. L. (1996). Patterns of behavior in endangered species preservation. *Land Economics*, pages 1–16.

Metrick, A. and Weitzman, M. L. (1998). Conflicts and choices in biodiversity preservation. *Journal of Economic Perspectives*, 12(3):21–34.

Morse-Jones, S., Bateman, I. J., Kontoleon, A., Ferrini, S., Burgess, N. D., and Turner, R. K. (2012). Stated preferences for tropical wildlife conservation amongst distant beneficiaries: charisma, endemism, scope and substitution effects. *Ecological Economics*, 78:9–18.

Moyer-Gusé, E. (2008). Toward a theory of entertainment persuasion: Explaining the persuasive effects of entertainment-education messages. *Communication Theory*, 18(3):407–425.

Newbold, T., Hudson, L. N., Hill, S. L., Contu, S., Lysenko, I., Senior, R. A., Börger, L., Bennett, D. J., Choimes, A., Collen, B., et al. (2015). Global effects of land use on local terrestrial biodiversity. *Nature*, 520(7545):45.

Nicholson-Cole, S. A. (2005). Representing climate change futures: a critique on the use of images for visual communication. *Computers, environment and urban systems*, 29(3):255–273.

Nielsen, M. R., Meilby, H., Smith-Hall, C., Pouliot, M., and Treue, T. (2018). The importance of wild meat in the global south. *Ecological Economics*, 146:696–705.

Öhman, A. and Mineka, S. (2003). The malicious serpent: Snakes as a prototypical stimulus for an evolved module of fear. *Current directions in psychological science*, 12(1):5–9.

Painter, J., Kristiansen, S., and Schäfer, M. S. (2018). How 'digital-born'media cover climate change in comparison to legacy media: A case study of the cop 21 summit in paris. *Global Environmental Change*, 48:1–10.

Richardson, L. and Loomis, J. (2009). The total economic value of threatened, endangered and rare species: an updated meta-analysis. *Ecological Economics*, 68(5):1535–1548.

Rick, S. and Loewenstein, G. (2008). The role of emotion in economic behavior. *Handbook of emotions*, 3:138–158.

Ruth, J. A., Brunel, F. F., and Otnes, C. C. (2002). Linking thoughts to feelings: Investigating cognitive appraisals and consumption emotions in a mixed-emotions context. *Journal of the Academy of Marketing Science*, 30(1):44–58.

Sakellari, M. (2015). Cinematic climate change, a promising perspective on climate change communication. *Public Understanding of Science*, 24(7):827–841.

Sergio, F., Caro, T., Brown, D., Clucas, B., Hunter, J., Ketchum, J., McHugh, K., and Hiraldo, F. (2008). Top predators as conservation tools: ecological rationale, assumptions, and efficacy. *Annual review of ecology, evolution, and systematics*, 39:1–19.

Sitas, N., Baillie, J., and Isaac, N. (2009). What are we saving? developing a standardized approach for conservation action. *Animal Conservation*, 12(3):231–237.

Skibins, J. C., Powell, R. B., and Hallo, J. C. (2013). Charisma and conservation: charismatic megafauna's influence on safari and zoo tourists' pro-conservation behaviors. *Biodiversity and conservation*, 22(4):959–982.

Slovic, P., Finucane, M. L., Peters, E., and MacGregor, D. G. (2007). The affect heuristic. *European journal of operational research*, 177(3):1333–1352.

Small, D. A., Loewenstein, G., and Slovic, P. (2007). Sympathy and callousness: The impact of deliberative thought on donations to identifiable and statistical victims. *Organizational Behavior and Human Decision Processes*, 102(2):143–153.

St John, F. A., Edwards-Jones, G., and Jones, J. P. (2011). Conservation and human behaviour: lessons from social psychology. *Wildlife Research*, 37(8):658–667.

Stamm, K. R., Clark, F., and Eblacas, P. R. (2000). Mass communication and public understanding of environmental problems: the case of global warming. *Public understanding of science*, 9(3):219–238.

Sunstein, C. R., Hastie, R., Payne, J. W., Schkade, D. A., and Viscusi, W. K. (2008). *Punitive damages: How juries decide*. University of Chicago Press.

Sunstein, C. R. and Nussbaum, M. C. (2004). *Animal rights: Current debates and new directions*. Oxford University Press.

Thomas-Walters, L. and J Raihani, N. (2017). Supporting conservation: The roles of flagship species and identifiable victims. *Conservation Letters*, 10(5):581–587.

Tisdell, C. and Nantha, H. S. (2006). Comparison of funding and demand for the conservation of the charismatic koala with those for the critically endangered wombat lasiorhinus krefftii. In *Vertebrate Conservation and Biodiversity*, pages 435–455. Springer.

Tisdell, C., Nantha, H. S., and Wilson, C. (2007). Endangerment and likeability of wildlife species: How important are they for payments proposed for conservation? *Ecological Economics*, 60(3):627–633.

Tisdell, C., Wilson, C., and Nantha, H. S. (2005). Association of public support for survival of wildlife species with their likeability. *Anthrozoös*, 18(2):160–174.

Tisdell, C., Wilson, C., and Nantha, H. S. (2006). Public choice of species for the 'ark': Phylogenetic similarity and preferred wildlife species for survival. *Journal for Nature Conservation*, 14(2):97–105.

Tobin, J. (1958). Estimation of relationships for limited dependent variables. *Econometrica: journal of the Econometric Society*, pages 24–36.

van der Linden, S. (2015). The conspiracy-effect: Exposure to conspiracy theories (about global warming) decreases pro-social behavior and science acceptance. *Personality and Individual Differences*, 87:171–173.

Västfjäll, D., Slovic, P., Mayorga, M., and Peters, E. (2014). Compassion fade: Affect and charity are greatest for a single child in need. *PloS one*, 9(6):e100115.

Verissimo, D., MacMillan, D. C., and Smith, R. J. (2011). Toward a systematic approach for identifying conservation flagships. *Conservation Letters*, 4(1):1–8.

Watson, D. and Clark, L. (1999). The panas-x: Manual for the positive and negative affect schedule-expanded form. https://ir.uiowa.edu/cgi/viewcontent.cgi?article=1011&context=psychology_pubs>[Accessed: 31 January 2018].

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.

YouTube (2018). Youtube for press. https://www.youtube.com/intl/en-GB/yt/about/press/ [Accessed: 31 January 2018].

2.7 Tables and Figures

Figure 2.1: Average donations made by individuals (Study 1, N=377)

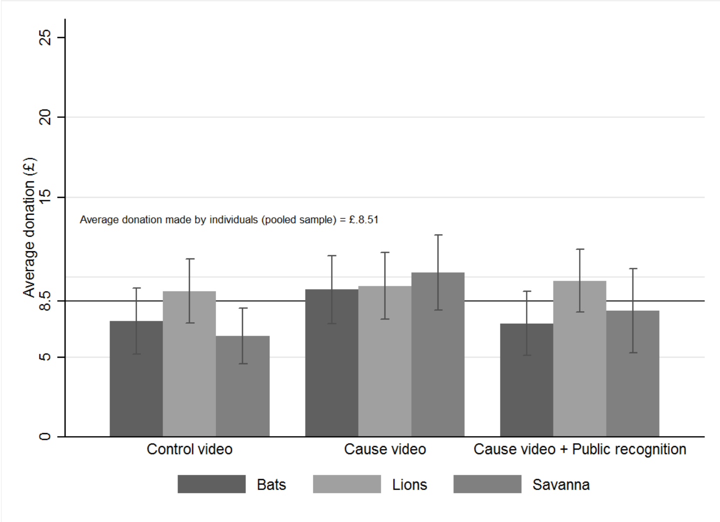


Figure 2.2: Share of individual donations over £0 (Study 1, N=377)

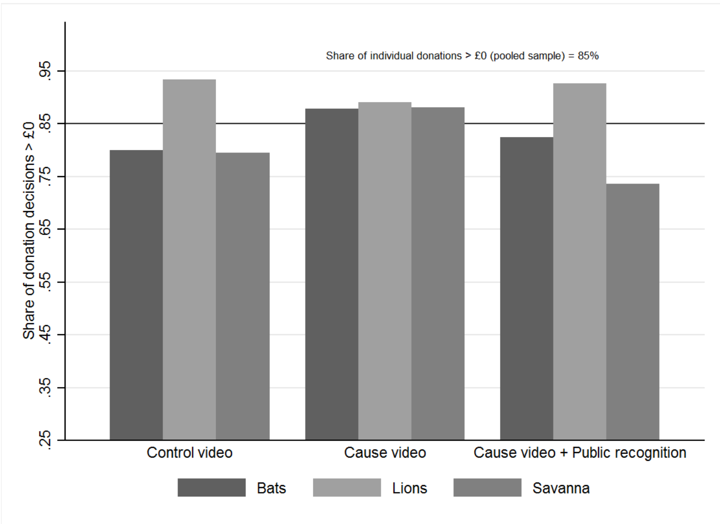


Table 2.1: Impact of Media Content on Donations in Study 1

Estimation method:	Tobit models		Cragg-Hurdle models							
Sample:			All				Past Donors			
Hurdle:			Probability	Amount	Probability	Amount	Probability	Amount	Probability	Amount
Regression models:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Species = 1, Lions	1.734**	1.903**	0.422**	1.484	0.428**	1.465	0.429*	1.082	0.425*	1.506
	(0.875)	(0.870)	(0.205)	(1.386)	(0.210)	(1.365)	(0.243)	(1.577)	(0.252)	(1.473)
Species = 2, Savanna	0.407	0.600	-0.127	0.873	-0.102	0.660	-0.138	1.025	-0.044	1.140
	(0.917)	(0.924)	(0.187)	(1.472)	(0.189)	(1.455)	(0.218)	(1.547)	(0.227)	(1.529)
Cause = 1, Human	2.150**	1.970**	0.160	3.292**	0.165	2.953**	0.241	5.412***	0.170	4.999***
	(0.905)	(0.929)	(0.203)	(1.416)	(0.205)	(1.392)	(0.235)	(1.535)	(0.237)	(1.411)
Cause = 2, Human + Recognition	0.594	0.208	-0.065	1.644	-0.085	1.084	0.104	4.116**	0.111	3.822**
	(0.936)	(0.915)	(0.204)	(1.538)	(0.206)	(1.489)	(0.237)	(1.719)	(0.239)	(1.579)
Constant	15.408	12.778	0.713	19.886	0.658	14.377	0.951	4.698	0.946	-2.988
	(14.816)	(14.875)	(3.528)	(21.822)	(3.405)	(21.882)	(4.314)	(23.873)	(4.054)	(24.912)
Observations	377	377	377	377	377	377	289	289	289	289
Session controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	No	Yes	No	No	Yes	Yes	No	No	Yes	Yes

Notes: Dependent variable: donations (£0-25), all models use robust standard errors clustered at the subject-level, with *** p<0.01, ** p<0.05, * p<0.1. The omitted group is Bats control video.

Table 2.2: Impact of Public Recognition on Donations in Study 1

Estimation method:	Tobit models		Cragg-Hurdle models							
Sample:			All				Past Donors			
Hurdle:			Probability	Amount	Probability	Amount	Probability	Amount	Probability	Amount
Regression models:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Public Recognition = 1, Public recognition	-1.569	-1.741*	-0.367	-1.465	-0.407*	-1.571	-0.233	-0.864	-0.176	-0.796
	(0.976)	(0.989)	(0.228)	(1.481)	(0.238)	(1.377)	(0.271)	(1.698)	(0.271)	(1.462)
Species = 1, Lions	1.627	1.929*	0.328	1.580	0.352	1.742	0.394	0.302	0.360	0.496
	(1.068)	(1.032)	(0.265)	(1.649)	(0.274)	(1.529)	(0.344)	(1.939)	(0.362)	(1.700)
Species = 2, Savanna	0.916	1.187	-0.208	1.951	-0.192	2.061	-0.242	1.517	-0.212	1.875
	(1.183)	(1.192)	(0.248)	(1.741)	(0.248)	(1.657)	(0.288)	(1.910)	(0.293)	(1.790)
Constant	12.618	6.053	5.037	-3.175	4.265	-13.512	30.048***	-14.891	29.147***	-28.605
	(24.916)	(24.768)	(4.912)	(31.968)	(4.729)	(31.241)	(3.653)	(32.548)	(3.345)	(33.315)
Observations	248	248	248	248	248	248	186	186	186	186
Session controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	No	Yes	No	No	Yes	Yes	No	No	Yes	Yes

Notes: Dependent variable: donations (£0-25), all models use robust standard errors clustered at the subject-level, with *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The omitted group is Bats control video.

Figure 2.3: Angry (Study 2, N = 177)

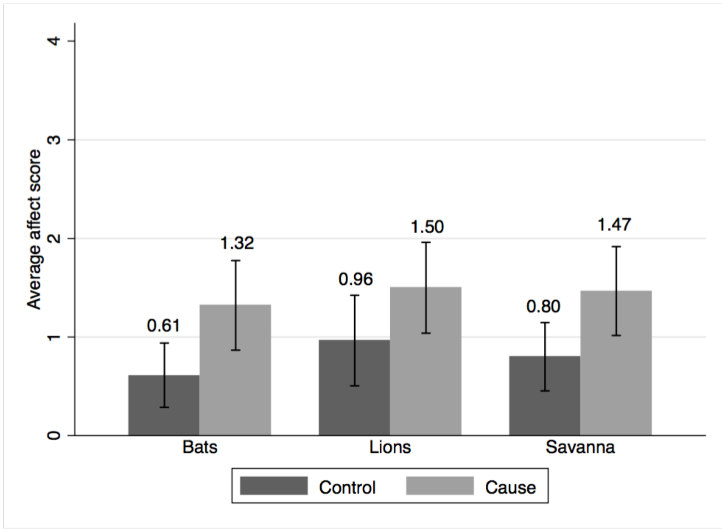


Figure 2.4: Sad (Study 2, N = 177)

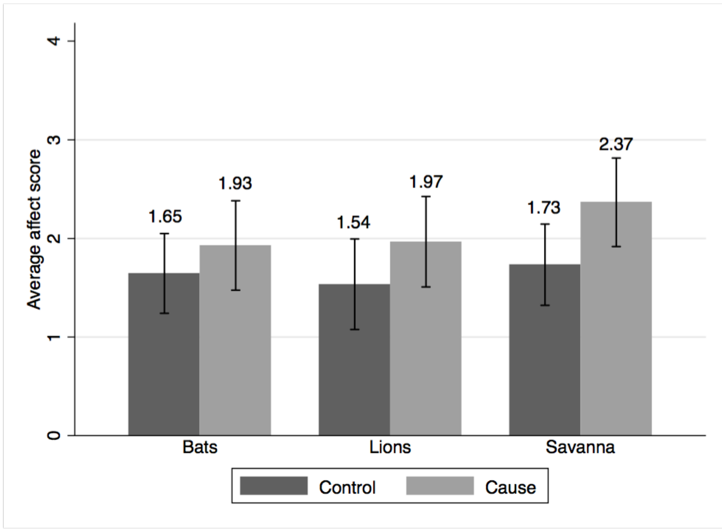


Figure 2.5: Guilty (Study 2, N = 177)

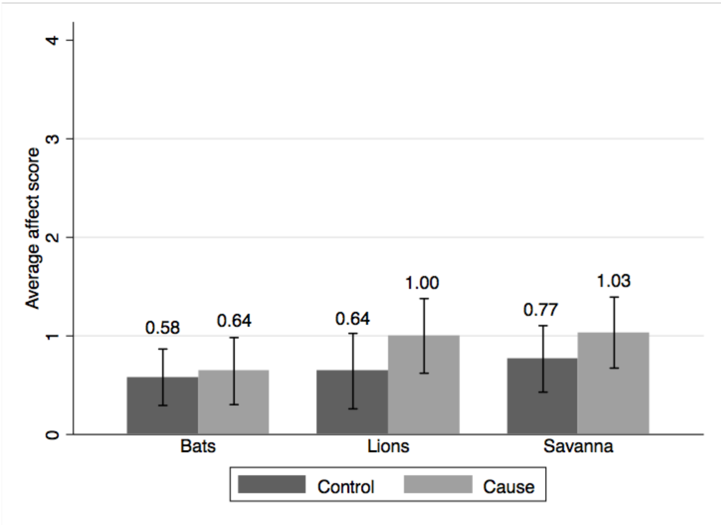


Figure 2.6: Sympathy (Study 2, N = 177)

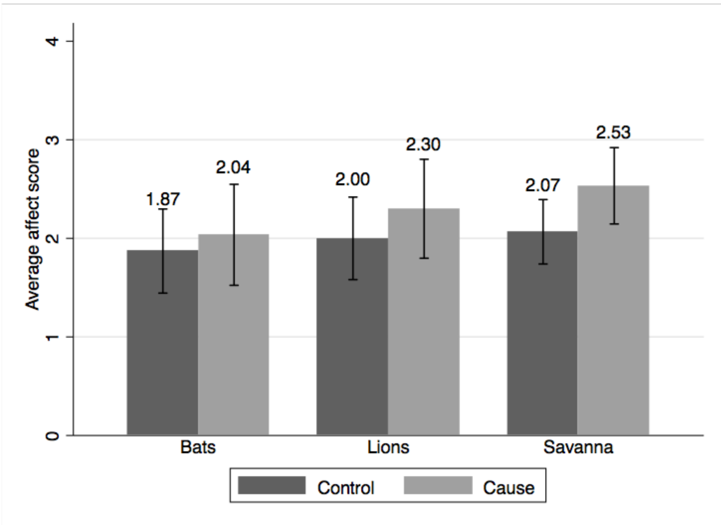


Figure 2.7: Happy (Study 2, N = 177)

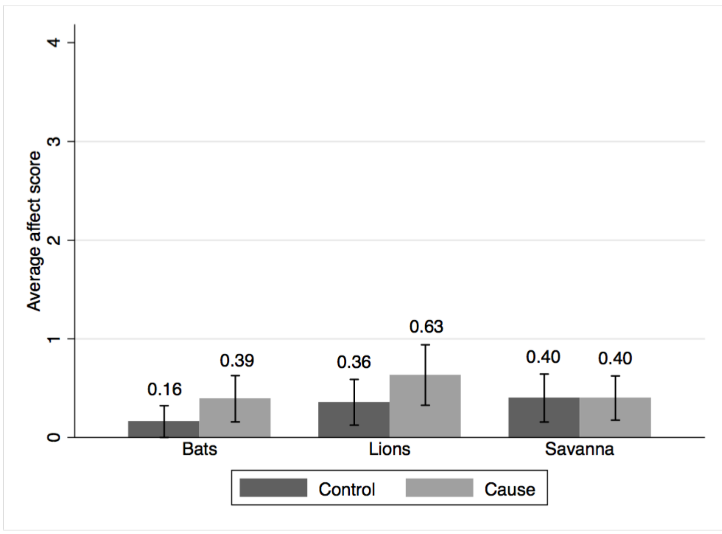


Figure 2.8: Calm (Study 2, N = 177)

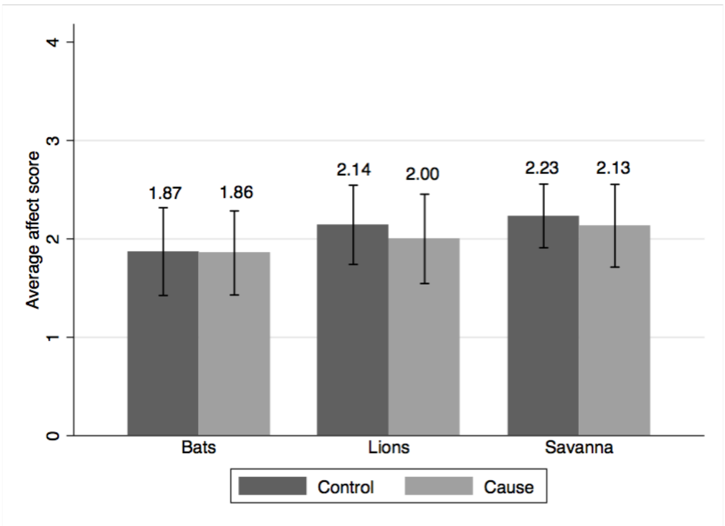


Figure 2.9: Interest (Study 2, N = 177)

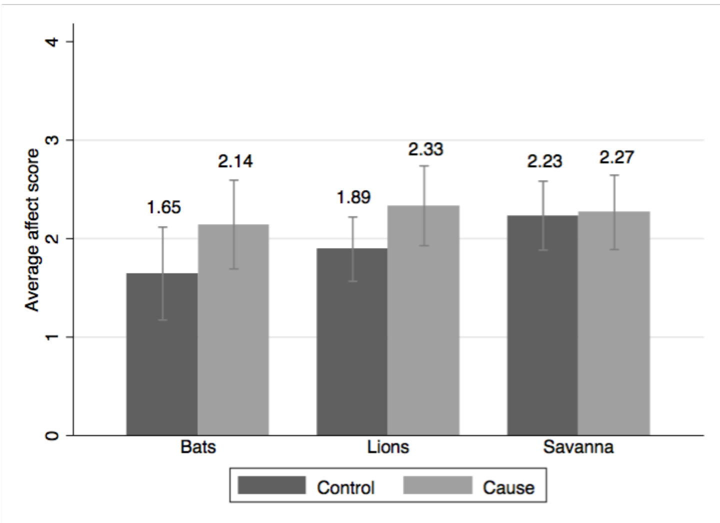


Table 2.3: Impact of videos on affect in Study 2

Dependent variables: Ordinal regression models:	Angry (1)	Sad (2)	Guilty (3)	Sympathy (4)	Happy (5)	Calm (6)	Interest (7)
Species = 1, Lions	0.347	-0.138	0.265	0.309	0.941**	0.471	0.470
	(0.398)	(0.377)	(0.392)	(0.376)	(0.439)	(0.388)	(0.376)
Species = 2, Savanna	0.498	0.464	0.709*	0.483	0.549	0.625*	0.791**
	(0.364)	(0.333)	(0.400)	(0.348)	(0.422)	(0.374)	(0.376)
Cause = 1, Human	1.050***	0.610**	0.433	0.656**	0.756*	-0.005	0.833***
	(0.330)	(0.293)	(0.311)	(0.310)	(0.398)	(0.295)	(0.313)
Observations	177	177	177	177	177	177	177
Session dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable: self-reported affect (None at all (0) to Extremely (4)); all models use robust standard errors clustered at the subject-level, with *** p<0.01, ** p<0.05, * p<0.1. The omitted group is Bats control video.

Chapter 3

Do biodiversity conservation videos cause pro-environmental spillover effects?

3.1 Introduction

Conservation organisations increasingly use persuasive audiovisual media like brief online videos to reach mass audiences. This strategy harnesses the growing tendency for the public to depend on audiovisual and digital modes of mass communication as a source of knowledge about environmental issues (Stamm et al., 2000; Doulton and Brown, 2009; Feldman et al., 2012; Gavin and Marshall, 2011; Schmidt et al., 2013; Sakellari, 2015; Vasi et al., 2015; Painter et al., 2018). Another reason that this strategy is vital is that most individuals are physically removed from conservation sites. There is also a shift towards sedentary activities involving electronic media comes at the expense of recreational choices located in nature (Pergams and Zaradic, 2008, 2006). But as noted by Waters and Jones (2011), there is much-untapped potential to leverage YouTube videos to float direct appeals for public involvement. But to take advantage these types of audiovisual tools and platforms, we need to understand both the direct and indirect effects that videos can have on individual decision-making.

As demonstrated in Paper 1, the narrative content of biodiversity conservation videos can have a direct effect on charitable donations. But they can also have unintentional, spillover effects on subsequent pro-environmental behaviours (PEBs) that are not the primary target of the video intervention. The conceptual framework of behavioural spillovers is useful to explore this possibility. It captures the notion that 'no behaviour sits in a vacuum' (Dolan and Galizzi, 2015). It recognises that an intervention may have unintentional effects on subsequent behaviours that are not directly targeted by it (Truelove et al., 2014). This framework allows us to consider whether the promotion of one pro-environmental behaviour (like watching videos and donating) raises the likelihood that individuals will adopt other PEBs in the following decision period (i.e., positive spillover), or reduces other PEBs (i.e., negative spillover) or even has no effect (i.e., no spillover). In the first case the intervention could be warranted, in the second case it needs reconsideration, and in the third case, we could have over-estimated its effects. The application of this tractable framework may be particularly useful in a conservation setting because organisations often try to amp up citizen engagement by following up donation appeals with smaller requests for future commitments.

Indeed, recent work documents that both positive and negative behavioural spillovers exist. Some studies show that audiovisual environmental media have a positive short-run impact on multiple PEBs, concern, attitudes, and beliefs (e.g., in Howell (2011)). But other studies show that engaging a pro-environmental behaviour may reduce later pro-environmental actions due to moral licensing, unintentional compensatory or offsetting effects. For example, Mazar and Zhong (2010) found people were more likely to act less altruistically and cheat, after buying green products compared to conventional products.[1] The underlying mechanisms driving the direction of these spillover effects is often unclear, and depend on the intervention context and individual characteristics. Moreover, whether biodiversity conservation videos (and the media content within them) cause pro-environmental spillovers, is an open empirical question, warranting further investigation.

This paper builds on and extends Paper 1, by examining if audiovisual media exposure from the biodiversity conservation videos and facing a donation task cause pro-environmental spillovers on two subsequent non-target behaviours: the Willingness to Pay (WTP) a green fee, and the Willingness to Donate (WTD) time to an environmental campaign. The first novelty of this paper is to extend the previous literature on media effects on behaviour by exploring the direct and indirect effects of both media exposure and content. In particular, we focus on media content about the anthropogenic cause of species endangerment. The second contribution is that we investigate if the similarity between PEBs (e.g., charitable donations of money and time versus willingness to pay a tax) impacts the likelihood of a positive spillover. We consider subjects' pro-sociality as a potential source of inter-subject heterogeneity, which can change the probability of a positive spillover effect between similar PEBs, such as revealed monetary donations and WTD time. As before, pro-social subjects are those who selected into altruistic environments in the real world, a more in-depth investigation into spillover effects of this sub-group is of academic and policy interest.

We found that both media exposure and content have direct and indirect effects on behaviour. Video content on the anthropogenic cause of endangerment increases the amount donated, but not the likelihood of donating. Video exposure increases the likelihood of a positive WTP green fee. We also found that past donors behave differently. They donated more when exposed to the anthropogenic cause of endangerment and were WTD more time when exposed to media content on the anthropogenic cause of endangerment. These findings convey that people's pro-environmental preferences and choices are endogenous to past choices interact with features of the behaviours themselves. Conservation organizations could also benefit by choosing to follow up requests with more similar types of behaviours.

In the next section, we locate our work in two strands of research: firstly, in studies seeking to quantify the behavioural impact of environmental films, and secondly, in studies about pro-environmental (and pro-social) behavioural spillovers. Section three outlines

[1]For example, moral licensing is one type of behavioural spillover and refers to the effect that when people initially behave in a moral or pro-social way, they are later more likely to display behaviours that are immoral, unethical, or otherwise problematic. See Blanken et al. (2015) et al for a review of the literature on moral licensing.

our experimental design, hypotheses, and procedures. Section four presents our results. Section five concludes with a summary of our key findings and discusses potential policy implications and directions for future research.

3.2 Related literature

3.2.1 Impacts of audiovisual environmental media

Audiovisual media can increase moral concern and pro-environmental behaviour (PEB), by communicating complex information quickly and memorably, using emotive images and narratives (Moyer-Gusé, 2008; Nicholson-Cole, 2005). Theoretical insights from economics and psychology suggest that audiovisual media can change behaviour through various conduits, such as increasing knowledge about the problem, and changing preferences, attitudes, beliefs and experienced affect about specific places, objects and issues covered in the video; and promoting the desirability of the pro-social action (La Ferrara, 2016; Howell, 2014; Nicholson-Cole, 2005; Pooley and o'Connor, 2000).

Previous studies reveal that environmental films can increase multiple PEBs, concern, attitudes, and beliefs, in the short-run (Balmford et al., 2004; Reusswig, 2004; Leiserowitz, 2004; Hart and Leiserowitz, 2009; Nolan, 2010; Jacobsen, 2011; Howell, 2011; Bahk, 2010; Greitemeyer, 2013; Howell, 2014; van der Linden, 2015; Janpol and Dilts, 2016; Arendt and Matthes, 2016). Most studies measure a range of PEBs and behavioural intentions using surveys, either before and after the film (within-subjects design), or after watching the film (between-subjects design). Sakellari (2015) and Howell (2014) provide recent reviews of the impact of climate-change cinema on PEBs, and DellaVigna and La Ferrara (2015) reviews quasi-experimental studies on how media impacts other social and economic behaviours.

Studies that focus on the impact of media exposure, i.e., watching an environmental documentary film, find positive short-term effects. For instance, Leiserowitz (2004) found that subjects who saw the 'Day after Tomorrow,' were more likely to state that they would donate money to or volunteer with a global warming group, apart from expressing greater risk perception, concern and worry about global warming. Nolan (2010), studied the impact of 'An Inconvenient Truth' and reported positive short-run effects on stated behavioural intentions to reduce personal emissions. Howell (2011) found 'The Age of Stupid' increased stated concern about climate change, motivation to act, and viewers' sense of agency (although these effects did not persist 10–14 weeks afterwards; also see

Howell (2014).

Janpol and Dilts (2016) and Arendt and Matthes (2016) are the closest to our study because they use a between-subjects experimental design to look at media impacts on contributions towards the environment. Both studies assign individuals to watch either nature or non-nature documentary films, after which each person could choose to donate to an environmental or non-environmental cause. Janpol and Dilts (2016) found that a higher proportion of subjects exposed to the nature documentary made a pro-environmental contribution, and Arendt and Matthes (2016) found a positive effect on donations, only for a sub-group who expressed greater connectedness to nature. In associated work, Jacobsen (2011) used a quasi-experimental approach and found 'An Inconvenient Truth' caused an increase in the purchase of voluntary carbon offsets.

Few related studies look at the impact of message content of climate change films and find mixed short-run effects. For instance, Greitemeyer (2013) found that watching a climate change sceptic film decreased environmental concern, whereas watching a climate change affirming film did not affect subject's concern. Similarly, van der Linden (2015) found that subjects were less likely to sign a global warming reduction petition, and were willing to volunteer less time and money after watching a climate conspiracy video.

We contribute to this body of literature in several ways. First, we extend the empirical evidence on how media affects PEBs to persuasive and brief online charity videos, within the realm of biodiversity conservation. Second, we quantify the separate impacts of media exposure to audiovisual information and additional audiovisual message content on donations, and two different stated behavioural intentions: namely to pay a fee and donate time. Also, we examine if behaviour varies across three different conservation videos, namely a charismatic species, a non-charismatic species and habitat, each with and without the anthropogenic cause of threat (therefore six videos in total), as a robustness check. Third, we consider how videos cause short-run behavioural changes using a spillovers framework, where we conceptualise that audiovisual media interventions targeting donations (direct effect), may unintentionally impact subsequent stated behavioural intentions (spillover effects). Thus, while previous work finds that audiovisual media affect multiple PEBs, we explicitly incorporate the sequential nature of pro-environmental decision making, into our analysis, as discussed below.

3.2.2 Pro-environmental behavioural spillovers

Previous experimental studies have quantified pro-environmental and pro-social behavioural spillovers, by exogenously varying price incentives, nudges, and information provision (e.g., in Alpízar et al. (2017b,a); d'Adda et al. (2017); Thomas et al. (2016); Lanzini and Thøgersen (2014); Poortinga et al. (2013); Baca-Motes et al. (2012); Thøgersen and Ölander (2003). Studies using experiments (and longitudinal surveys), with sequential decision tasks show mixed results, demonstrating negative, positive or no spillover effects. We refer the reader to Nash et al. (2017); Truelove et al. (2014) and Dolan and Galizzi (2015), for recent reviews from environmental psychology and economics.

Studies examining spillover effects of audiovisual information are closer to this article. These studies primarily focus on how specific 'incidental' emotions caused by the emotion-arousing video clips, which are unrelated to the subsequent decision task, impact behaviour (Hanley et al., 2017; Andrade and Ariely, 2009; Harlé and Sanfey, 2007; Lerner et al., 2004). For instance, Harlé and Sanfey (2007) found lower acceptance rates of unfair offers, when subjects were exposed to movie clips eliciting sadness. Andrade and Ariely (2009) exposed subjects to films that cause either happy or angry affective states, followed by a series of sequentially designed Ultimatum and Dictator games. They found that subjects exposed to film clips eliciting anger were more likely to reject unfair offers and make fairer offers in both games, highlighting the potential importance of behavioural consistency. On the other hand, Hanley et al. (2017) found no impact on willingness to pay to improve coastal water quality and fish populations, when subjects were exposed to film clips arousing, happy, sad or neutral emotion states. We extend this body of work, by considering if environmental film clips intentionally designed to increase donations, cause PEB spillovers.

We also attempt to shed light on whether behavioural similarity affects both the direction and existence of PEB spillovers. Previous research suggests that a higher perceived degree of similarity between different behaviours can influence spillover effects (Thøgersen, 2004), but few studies systematically examine this (Truelove et al., 2014; Dolan and Galizzi, 2015). For instance, a positive spillover is more likely if individuals are prone to co-perform similar behaviours (Gatersleben et al., 2002), or if they act to prevent cognitive dissonance, or have preferences for behavioural consistency (Bem, 1972; Thøgersen, 2004). More specifically, Thøgersen (2004) noted that if individuals perceive that two behaviours are linked to a common goal, individuals might experience cognitive dissonance when performing one, and not the other. In addition, an individual's self-identity can be strengthened when she undertakes consistent choices in a specific domain, which may lead to behavioural consistency within that domain (Van der Werff et al., 2013; Whitmarsh and O'Neill, 2010). In one of the few studies on the topic, Margetts and Kashima (2017) found that positive spillover effects were more pronounced for behaviours that required similar money resources (between green shopping and willingness to pay a green fee) than for the behaviour that demanded dissimilar resources (between green shopping that required money and willingness to donate time to a charity).

On the other hand, there may be a negative spillover between similar behaviours, if subjects have a weak pro-environmental or pro-social identity (Whitmarsh and O'Neill, 2010; Truelove et al., 2014). Fishbach et al. (2006) propose that behaviours within a domain may be perceived as substitutes, so that the successful performance of the first behaviour might be regarded as having done enough to move towards the goal, reducing the need to perform the second goal-related behaviour. Another mechanism facilitating negative spillovers is the 'self-licensing' or 'moral licensing' effect, where an individual's inclination to engage in moral behaviours decreases after undertaking the previous sustainable behaviour (Clot et al., 2016; Mazar and Zhong, 2010; Sachdeva et al., 2009). There is experimental evidence of negative spillover effects within the same behavioural domain and across behaviours with great similarity. Within electricity conservation, Noblet and McCoy (2017) found individuals who engaged in past sustainable energy behaviours are less likely to support proposed energy efficiency/renewable energy policy investments. Brañas-Garza et al. (2013) found donations in the previous period negatively affected present decisions in a sequence of dictator games that tested pro-social behavioural spillovers. These findings lend empirical support for the simultaneous existence positive and negative spillovers (Thøgersen and Ölander, 2003; Effron and Monin, 2010).

We contribute to this work, by mapping the spillover effects from videos across different classes of pro-environmental behaviours of varying degrees of similarity. We focus on whether positive spillovers occur within the same behavioural domain of charitable donations, compared to the willingness to pay a green fee. The latter can be perceived as stating policy support for mandatory tax payment and is arguably dissimilar to giving money and time, which are two types of voluntary contributions (albeit measured in different resource units). In support of this, Duncan (1999) theoretically predicts that volunteering time and money can be perfect substitutes for contributors to the public good. Carpenter and Myers (2010) also provide experimental evidence that donations of money and time are correlated in a sample of fire-fighters (also see Bauer et al. (2013) for similar evidence from cross-country surveys). Other studies point out that volunteering time and money is perceived differently from the willingness to pay a green tax due to the compulsory 'push' element of regulatory coercion associated with taxes, which in turn can have behavioural implications (Drews and Van den Bergh, 2016; Steg et al., 2006).

In related work, Clot et al. (2016) found that inducing environmentally-orientated students to imagine a compulsory commitment to a virtuous act (called the 'regulatory condition') resulted in a licensing effect. More precisely, individuals donated less money to an environmental cause, compared to those subjects who imagined a voluntary commitment to an environmental program (non-regulatory condition) and a control condition (no commitment to any virtuous act was imagined). They also find that environmental-orientated students donated significantly more than business-orientated students in the non-regulatory condition. We extend this work, by considering if there are spillover effects from money donations (voluntary contribution) to the willingness to pay a fee (coercive tax regulation) to the willingness to donate time (voluntary contribution). By doing so, we attempt to recreate a sequence of three separate environmentally- relevant decisions, to trace whether individuals reverse or enforce previous environmental and moral behaviour, across different behavioural domains. We also pay careful attention to whether pro-social subjects show positive spillover effects from watching videos and donating money, to giving time. We describe our experimental design and procedures in more detail in the following section.

3.3 Experimental design

3.3.1 Experimental design and hypotheses

We follow Truelove et al. (2014) to define a behavioural spillover as the effect of an intervention on subsequent behaviours not targeted by that intervention. Panel A in Table 3.1, describes the three behaviours, which are the outcome variables in our study. Behaviour one is charitable donations of money (Donations) and is the target of the intervention. Behaviour two is the stated Willingness to Pay a green tax (WTP), and behaviour three is the stated Willingness to Donate time to an environmental campaign (WTD time). In line with Dolan and Galizzi (2015), we conceptualise that the behaviours take place sequentially, i.e., behaviour one is followed by behaviour two, and then behaviour three. Table 3.1, Panel B summarises the between-subjects 'add-on' experimental design.

[Table 3.1]

Subjects are randomly assigned to a No Video condition, or to watch one of the different videos, without or with the anthropogenic cause of endangerment (called Control Videos and Cause Videos conditions respectively). In the No Video group, we directly elicit the WTP a green fee and then the WTD time from subjects. In the Control Video group, the baseline videos contain conservation-relevant information (for example the ecological role and conservation status of each species, described in detail in the next subsection). In the Cause Video group, we add audiovisual information on the anthropogenic cause of threat to each baseline video. After subjects watch the video, we elicit charitable donations, using an incentive-compatible modified dictator game, followed by the stated WTP a green fee and then the WTD time, as described in the following subsections. This design allows us to compare potential differences in donations, WTP a green fee and WTD time between subjects in different treatment groups, to yield direct and spillover treatment effects of media interventions.

We formulate three hypotheses based on the literature reviewed in the previous section. First, we consider the direct treatment effect of media content describing the anthropogenic cause of endangerment, on donations. We build on the insight that additional textual information on the human-made causes of bio-diversity depletion increases the stated WTP to undo the harm caused (Bulte et al., 2005; Brown et al., 2002; Kahneman et al., 1993). For instance, Bulte et al. (2005) find that Dutch respondents are willing to state a higher WTP to protect seals when they appear to be threatened by human-made factors, such as oil and gas drillers, or by the greenhouse effect. Assuming audiovisual messages on the human-made causes of species depletion has a similar impact on donations:

Hypothesis I: Exposure to media content about the anthropogenic cause of endangerment, has a positive direct effect on contributions, i.e., Δ DonCause = DonCause Video – DonControl Video > 0.

Now we consider two of types of spillover effects on the WTP fee and WTD time. First, we explore the spillover effect of media exposure to videos aiming to increase donations and donating (between subjects with No Video, Control Video, and Cause Video groups). Second, we look at the spillover effect of media content on the anthropogenic cause of threat, conditional on having been assigned to one of the Videos and facing a donation task (between subjects in Control Video and Cause Video groups). While the former measures the unintended effect of exposure to a charity video (and facing a costly donation decision), the latter measures unintended consequences of a specific type of campaign message, controlling for the baseline audiovisual conservation information. Given the mixed results in the previous literature (e.g., in Janpol and Dilts (2016); Arendt and Matthes (2016); Howell (2014); Greitemeyer (2013), we formulate and test a null hypothesis of no spillover effect from media exposure and content on WTP:

Hypothesis II: There is no spillover effect from biodiversity conservation videos on WTP a green fee or WTD time. More specifically, there is:

Hypothesis II-A: Media exposure has no spillover effect: ΔWTPVideo — D = WTPVideo — D – WTPControl = 0 and Δ WTDVideo — D, WTP = WTDVideo — D, WTP – WTDControl — WTP = 0.

Hypothesis II-B: Media content on the anthropogenic cause of endangerment has no spillover effect: Δ WTPCause — D = WTPCauseVideo — D – WTPVideo = 0 and Δ WTDCause — D, WTP = WTDCauseVideo — D, WTP – WTDVideo — WTP = 0.

However, as discussed previously, positive spillovers may be more likely if there is a higher similarity between two behaviours if subjects have preferences for consistency or hold a stronger pro-social identity (Thøgersen, 2004; Truelove et al., 2014; Margetts and Kashima, 2017). In our experimental set-up, there is arguably more similarity between money donations and WTD time as they are both pro-social actions. Subjects who donated to charities in the past are demonstrably more pro-social than those who have not, by already selecting into altruistic environments in the real world. Notably, previous work has shown that pro-sociality measured in the lab predicts behaviour in the field (Benz and Meier, 2008) and that pro-social preferences are stable over long periods of time (Carlsson et al., 2014; Volk et al., 2012). Thus, it is possible that past donors may perceive the greater similarity between charitable donations and WTD time, leading to the higher likelihood of positive behavioural spillovers on WTD time, for these pro-social subjects. We test the following hypothesis:

Hypothesis III: Media exposure and content have a positive spillover effect on WTD time amongst pro-social subjects, i.e., subjects who report donating to charity in the past.

3.3.2 Experimental procedure

All sessions were run at the London School of Economics Behavioural Research Lab (LSE BRL) during November to December 2016. The experiment was hosted on the Qualtrics platform. We followed a double-blind experimental procedure, where subjects were randomly assigned to a computer terminal upon arrival, after which the computer program randomly assigned each subject to one treatment group. Participation was open all individuals registered at the LSE BRL to obtain a heterogeneous subject pool and an adequate sample size for all treatments. In total, 259 subjects participated, and each treatment group had an average of 37 subjects. Each subject was paid a £5 show-up fee that they could collect at the end of the experiment. Apart from this, all subjects had an equal chance to earn a maximum of £25 from the charitable giving task, but only one subject was randomly selected in each session to receive this payout. Such lottery methods to determine payment have been used in other studies such as Clot et al. (2016). Moreover, in a recent paper, Charness et al. (2016) review a series of experimental games (including dictator games) and find that paying one or paying all subjects in a session results in qualitatively similar behaviour.

3.3.3 Video interventions

Existing videos had not been designed to provide conservation-relevant information in a controlled manner suitable for this experiment's objectives. Thus, we constructed three standardised Control Videos, featuring a non-charismatic species (Bats), a charismatic species (Lions) and a composite habitat composed of the two species (Bats and Lions in the Savanna). Each video had a sequence of fifteen photographs for each species/habitat, with a standardised voice-over, first introducing the species/habitat, the ecological role of each species, it's conservation status, and a line that habitat loss due to land conversion, is a cause of endangerment.[2]

The Cause videos are identical to the Control Videos, barring one additional photo and a line of voiceover stating that another important cause of species decline is hunting and poaching. This is useful for numerous reasons. Firstly, understanding how responses to information about human-made drivers of endangerment are critical to generate greater awareness about the nature of the Anthropocene and associated environmental problems (Dirzo et al., 2014; Waters et al., 2016). Secondly, hunting is an unambiguous anthropogenic cause of biodiversity loss and can invoke moral assessments of right and wrong (Fischer et al., 2013). The issue of hunting is also underrepresented in the environmental and conservation behaviour literature (St John et al., 2011). Importantly, hunting and illegal wildlife trade is a consistent cause of species decline for both species considered (IUCN, 2016). Following the procedure outlined in (Gross and Levenson, 1995), subjects were exposed to a blank screen for 20 seconds, followed by the conservation appeal, lasting for an average length of 150 seconds.[3]

[2]See Appendix G for supplementary materials.

[3]After this, we also elicit stated affect from the video clip, which is analysed in greater detail in chapter 2.

3.3.4 Donations

After subjects were exposed to the video, they were directed to a donation page, which carried one photo of the species/habitat featured in the , and instructions for the donation task. We adopt a modified dictator game used in other charitable giving experiments (e.g. in Eckel and Grossman (1996). An endowment of £25 was given to each subject. Subjects could choose to allocate any part of this endowment) to the African Wildlife Foundation, a conservation charity (in £1 increments). We chose an endowment of £25 because it is a frequently suggested donation amount by conservation charities and of sizeable economic magnitude (five times the show-up fee). This incentive-compatible design increases to cost of being pro-social to all subjects facing the donation task, but holds the cost itself fixed across subjects across treatment groups. We adopt several design features to make the decision setting more realistic: for instance, donations go to conserve the same public good, i.e., vulnerable African species and their habitats. Also, the instructions informed the subjects that they would be sent a payment receipt if they so desired, upon writing down their lab identification code and postal address.

3.3.5 Willingness to Pay (WTP) a green fee

Subjects stated their WTP a green fee after watching one of the videos and making their donation decision. Conversely, subjects in the No Video condition, were directly exposed to the question on the WTP a green fee. The proposed tax was an additional fee per disposable cup of hot beverage on the LSE campus and could lie between 0 to 100 pence per cup. Any revenue raised would be earmarked for environmental sustainability projects on the LSE campus. We emphasized consequentiality to reduce hypothetical bias, by stating that their responses would be used to inform LSE's sustainability policy (Bulte et al., 2005). We also used an entreaty to promote truth-telling through the following message: 'Please provide your honest answer' and 'While answering, please consider how many hot drinks you buy at LSE in disposal cups and how much that extra charge will affect you' (Loomis, 2014). Subjects could select any amount between 0 to 100 pence in one penny increments using a slider task (default was set to 0 pence). To control for potential sources of individual heterogeneity, we asked two control questions, after subjects stated their WTP. The first question asked how often they bought hot beverages on the LSE campus, on a Likert scale of 1 (Never) to 7 (Always). The second question asked how often subjects used reusable beverage cups, on a Likert scale of 1 (Never) to 5 (Always).

3.3.6 Individual attributes

Next, subjects answered questions about whether they had donated previously to charity, to obtain a measure of how pro-social they were.[4] Subjects also answered three self-assessment questions measuring PEBs, on how often they bought eco-friendly products, organic/local/seasonally grown food and how often they recycled. The responses were measured using Likert scales from 0 (Never) to 4 (Always). Each subject's answer to these three questions was averaged to form a single PEB score, in order to capture to what extent subjects engage in previous behaviours. We collected socio-demographic characteristics, such as age, gender, whether they were full-time students, and their affiliation to the LSE.

3.3.7 Willingness to Donate (WTD) time

Lastly, we measured the WTD time to an environmental campaign, which is the second non-target behaviour in our experimental set-up. After subjects answered questions on individual attributes, the experiment ended with a question on whether and how much time subjects would be willing to volunteer to organize events to raise awareness of environmental issues on campus in the following semester. They had to indicate their willingness to donate time by choosing a number between 0 to 7 hours using a slider task (where the default was set to zero).[5]

3.3.8 Sample

Of the total sample, 63.71% was female and had an average age of 24 years. Eighty point three one percent (80.31%) were full-time students, and 73% were affiliated to the LSE (in Appendix C, C.1). There was balance across individual attributes by treatment group, and shows balance on most attributes, barring age (one group elicited slightly older people). As we follow a double-blind random assignment, this is likely due to chance (Table

[4]Another option would be to as subjects whether they consider themselves pro-social, to get a self-assessment measure of their identity. We did not want to prime the subjects to be pro-social by asking them before the video and were concerned measures elicited after watching the video would be biased. Thus, we prefer to use a survey measure of revealed behaviour, by directly asking subjects if they had donated to charity previously.

[5]A possible concern is that the WTD time elicited here captures the stated intention to donate time to an *unspecified environmental campaign* on the LSE campus next semester. As the treatment is perfectly random, any difference in the stated intention across groups should capture the spillover effects. But the effects should be interpreted with caution if subjects are unclear what they are donating their time to, or what they are 'buying' with their time. For instance, the measure may be possibly affected by hypothetical bias, which could service to inflate the WTD time measure and the size of the spillover effect.

C.2 in Appendix C).

3.4 Results

After describing our estimation strategy, we report our main results in three subsections, corresponding to each hypothesis, i.e., direct effect on donations, spillover effects on WTP and WTD, and heterogeneous spillover effects by pro-social subjects, i.e., past donors.

3.4.1 Estimation strategy for direct and spillover effects

We used the linear two-part Cragg-Hurdle model to estimate impacts on bounded outcomes (Cragg, 1971), due to the nature of our outcome variables and experimental set-up. For instance, when we estimated the treatment effects on charitable donations, the first part of the Cragg-Hurdle model deals with the decision of whether to donate (i.e., the first hurdle is the decision to give a non-zero amount) and was estimated using a probit regression model. The second part deals with how much to donate (i.e., the unbounded outcome), which is estimated by using a truncated linear regression model.[6] We applied similar reasoning to determine the treatment effects on WTP a green fee and WTD time.

This estimation strategy yielded several advantages over standard statistical tests. First, it allowed us to consider the distinct causal effects of each treatment variable on the probability of donating a non-zero amount (Probability) as separate from the decision of how much to give (Amount). While previous experimental evidence from dictator game experiments does find distinct treatment effects on donation probability and amount (Engel, 2011), how media exposure and content impact the two-part decision is an open empirical question. Second, it allowed us to control for potential session-fixed effects, by adding session dummies. In addition, we added another covariate for the number of subjects per session, to control for any variation in the expected payout from the donations game, which may in turn impact donations and spillover effects. We also used robust standard errors-clustered at the subject-level. Third, it allowed us to control for individual heterogeneity as an additional robustness check, by using individual-level covariates (such as age and gender). In the following subsections, we restrict our attention to discussing the impact of media exposure and content in the text, and present results for the pooled Cragg-Hurdle regression models (with dummies to control for each video type, i.e., Bats,

[6] The Cragg-Hurdle model treats the first hurdle i.e., donations of zero currency units, as an observed value of behavioural and policy interest rather than censored or selected variable values; it is preferable to alternatives like the Heckman selection model (Wooldridge, 2010). The estimation strategy is explained in the Appendix B.

Lions, Savanna).

3.4.2 Direct effect on donations: Media content on anthropogenic cause of endangerment

Average contributions for the pooled sample were about £8.72 or 34.88% of the endowment (the median and mode = £5).[7]. While it is possible that higher offers in our experiment were due to media exposure, we do not have another subject group which did not watch any film, so it is difficult to conclude this was the case. In total, 13.45% of the sample chose to zero-donations. From Figure 3.1, we see average donations are higher for subjects exposed to Bats and Savanna Cause Videos, and Lions groups (around 39-40% of endowment), providing suggestive evidence that media content positively impacts donations.

[Figures 3.1]

Table 3.2 presents results of the Cragg-Hurdle model on donations, with session and video controls. The explanatory variables of interest are a treatment dummy for Cause Videos, with the omitted category being the Control Video group. From model (1), there was no impact on the probability of donating a non-zero amount. But in Model (2), media content on the anthropogenic cause of endangerment increased the amount given, conditional on having decided to donate (significant at 5%). This result implies that additional media content from Cause videos elicits higher donations by around £2.05, relative to the control videos. Given the lower threshold for contributions on many charity's websites are £5, the effect size is of relatively sizeable magnitude, especially when scaled across a large population. Thus, we find confirmatory evidence for the hypothesis of the positive effect of media content on donations, in line with insights from previous studies (e.g., in Bulte et al. (2005); Kahneman et al. (1993)).[8]

[Table 3.2]

[7] This figure is close to but marginally higher, than offers in charitable giving experiments, such as 30% in Eckel and Grossman (1996), but higher than offers made in anonymous dictator games of around 20% in Camerer (2003).

[8] When we add individual controls in Table C.3, the significance on the Cause variable falls, although none of the individual covariates are significant (barring full-time student status, which is positive and significant at 5%). The Lions videos increase the probability of donating in all specifications (weakly significant at 10%).

3.4.3 Spillover effects on WTP a green fee and WTD time: Media exposure and media content

Figure 3.2 presents the average WTP green tax by treatment group, and the average WTP a green fee for the pooled sample is 22.72 pence (median = 20 pence). Figure 3.3 presents WTD time to a campaign. We found that the average for the pooled sample is around 2.34 hours (median = 2 hours). In Table 3.3, models (1, Probability) and (2, Amount), provide the results of the effect of media exposure to either the Control or Cause Video on WTP, with session and video controls. Model (1) shows that when subjects are exposed to any video, they were more likely to state a positive WTP, relate to the no video control group (significant at 1%). In addition, model (2) demonstrates that there is a weak positive effect on WTP amount, conditional on having decided to state a positive WTP (significant at 10%). This finding is in line with previous literature, such as Janpol and Dilts (2016) and Howell (2011), who also found that exposure to environmental films can increase stated the intention to engage in future PEBs and elicit more support for green policies. However, we found that spillover effects are more robust on the probability of choosing to pay a fee, rather than the amount.

[Figures 3.2 and 3.3] [Table 3.3]

On the other hand, Models (3) of the Probability, and (4) of the Amount, indicate that on average, there is no spillover effect on WTD time, for the pooled sample. This result suggests that the extent to which the impact of the charity videos can carry over to impact subsequent PEBs may be limited.[9] Our results are robust to the inclusion of (i) session controls in the main models (ii) the addition of individual controls (iii) behavioural lags, including donation and WTP, and (iv) replicating analysis with separate discrete choice Probit, models, and Tobit and OLS regression models. The robustness estimates provide qualitatively similar results, but are omitted for brevity, and are available on request.

In summary, although we did not observe a negative spillover effect on WTD time, we did not see positive spillover effects either. More generally, these results reveal only a modest impact of media on pro-environmental behaviour, unlike studies which document changes in a far more extensive range of PEBs after exposure to environmental films (e.g., in Howell (2011) and Leiserowitz (2004)). There are several potential reasons for

[9]From Table C.4, when we add individual controls to model (7), we find that media content on anthropogenic cause of endangerment increases the probability of stating a positive WTD time (significant at 5%). We also find that a higher PEB score is associated with a positive probability of stating a positive WTP (significant at 1-5%), and positive with amount and probability of stating WTD (significant at 1%).

this, although it is difficult to conclude why this is the case. Firstly, unlike many previous studies that use cross-sectional or before-and-after surveys and a self-selected sample, our experimental design followed sequential behaviours and allowed us to map how past decisions impact future choices. Given this, our findings suggest that after subjects undertake the money donations task and state their WTP a green fee, there is no spillover effect of videos on WTD time. Relatedly, real monetary stakes may have dampened subsequent stated behavioural intentions, by increasing the salience of money to crowd out moral motives (Bolderdijk et al., 2013) or by reducing hypothetical bias (Lönnqvist et al., 2011; Harrison, 2006). Secondly, our experimental design incorporated brief conservation videos rather than full-length documentary films that can arguably have a weaker effect on behaviour.

3.4.4 Heterogeneous spillover effects

We explored subgroup variation in a regression framework used in previous work such as Heckman et al. (1997, 2002), Djebbari and Smith (2008) and Ferraro and Miranda (2013). More specifically, we considered the interactions terms between the treatment variables (i.e., media exposure effects by dummy variables for No Video, Control and Cause Videos, or media content by a dummy for Control and Cause Videos) and the donor dummy, which switches on if subjects donated to charities in the past. We ran independent regressions for the donor sub-group covariate, following Heckman et al. (2002), continued using the Cragg-Hurdle model as before, with session and video controls, and clustered robust standard errors at the subject-level.

In total, 74.51% had donated to charities in the past and were considered ‘pro-social’ subjects for this study. We tested if these pro-social subjects were more likely to show a positive spillover effect on WTD time, by first considering the direct effects on donations, presented in Table 3.2, models (3) and (4). We found that the coefficient on the interaction term between Past Donor and Cause Video increased in magnitude, and is significant at 5%. This result indicates that pro-social subjects are especially sensitive to messages on the anthropogenic cause of endangerment, relative to non-donors, controlling for other covariates (this result is robust to the addition of individual controls). Secondly, we found that - controlling for other covariates - pro-social subjects donated lower amounts relative to those who did not donate in the lab. One explanation for this is that subjects state lower donation amounts in the lab because they engage in more pro-social activities in the real world. Another possibility is that pro-social subjects become ‘reluctant sharers’ in the lab, i.e., they demonstrate lower levels of pro-social behaviour when they cannot remove themselves from the sharing opportunity in the donation task (Lazear et al., 2012).

[Table 3.4]

Next, we considered spillover effects on WTP a green fee and WTD time, in Table 3.4. As per our hypothesis, we found that the interaction term between the Cause Video and Past Donor dummy had a positive and significant effect on the amount donated (conditional on deciding to donate), in models (4) and (8). This finding lends empirical support to the idea that positive spillovers from media exposure to Cause Videos and media content on the anthropogenic cause of endangerment are more likely, between similar behaviours, when subjects are more pro-social. It is in line with studies which highlight that heterogeneity across individuals impacts measured spillover effects (e.g., in Clot et al. (2016), as well as impacts of the media (e.g., in Arendt and Matthes (2016)). This finding is also in line with literature which highlights that self-identity plays a vital role in influencing behavioural change (e.g., in Van der Werff et al. (2013); Whitmarsh and O'Neill (2010). However, we did not find a similarly positive and significant effect on the interaction term between Control Video and Past Donor. This suggests that videos with narratives that draw attention to the negative impact of humans on the environment may have a spillover effect of larger magnitude, amongst this sample. These results are also robust to the addition of individual controls, and to restricting observations to the sub-sample of donors.

3.5 Discussion and conclusion

Online and digital audiovisual media have a crucial role in increasing awareness and support for conservation, and more broadly, in fostering environmental education. Thus, understanding the direct and spillover effects of media exposure and content represents a valuable research enterprise. Interestingly, relatively few studies have examined how media affects PEBs, using a spillovers framework. Most studies on how audiovisual media impacts behaviour demonstrates that there can be positive (albeit) short-run effects on multiple PEBs, and behavioural intentions. Others have shown that specific types of message content also can impact intentions negatively (e.g., climate conspiracy videos), or have no impact. The bulk of past research moreover focuses on measuring multiple PEBs in a self-selected sample and primarily focus on climate change films, especially documentaries.

We contribute to the literature on how media impacts environmental behaviour by using the conceptual framework of behavioural spillovers. More specifically, we map the sequential nature of decision making to examine how media exposure and content can have distinct spillover effects in the short-run. We drew from the literature on PEB spillovers, which have not yet, to our knowledge, examined spillover effects of audiovisual media on biodiversity conservation. Thus, we have attempted to bring together these two lines of research, to map out the direct and spillover effects of media exposure and content of brief biodiversity conservation videos.

We provide initial evidence that people can behave consistently, generating positive spillovers, when exposed to media about biodiversity conservation. Moreover, unintended positive effects persist from exposure to media content on the anthropogenic cause of endangerment, when behaviours are more similar, and subjects are already pro-social. These results are broadly consistent with previous research on pro-social and pro-environmental behavioural spillovers, as well as on the impacts of audio-visual media. However, they document more modest impacts of brief videos on multiple PEBs than previous studies.

We found that media exposure caused positive spillover effects on the WTP a green fee, by increasing the probability of subjects donating a positive amount, but there are limited effects on the WTD time. We also found that media content on the anthropogenic cause of endangerment engenders positive spillover effects on the amount of time subjects are willing to donate (conditional on having decided to give) for pro-social subjects. This result provides initial empirical support, which greater similarity between subsequent behaviours, such as monetary donations and WTD time, can engender positive spillovers for pro-social individuals. In addition, it highlights that audiovisual information effects are heterogeneous.

These findings hold some potential policy implications. Firstly, exposure to audiovisual media can have positive or no spillover effects on subsequent PEBs, suggesting conservation organisations can follow up donation requests, with smaller requests on behavioural intentions. Secondly, we iterate that special care must be paid to design of media content, and the narratives presented in videos as noted in Paper 1 for the additional reason that they can have spillover effects. Information on the anthropogenic cause of endangerment is a promising avenue to consider to raise PEBs and behavioural intentions. Lastly, follow-up requests that are more similar to previous behaviours (e.g., money donations and WTD time) may yield positive spillover effects amongst donors.

That said, our findings must be seen with caution for a couple of reasons. Our methodological approach of using a lab experiment yields the advantage of having greater control over media exposure and content, and in the mapping of different behaviours sequentially. However, there are concerns regarding external validity, if the findings from within the lab do not translate qualitatively in the field context. We attempt to engage with this issue, by explicitly examining how pro-social subjects behave in the lab, given the existing evidence on the stability of social preferences in the lab and the field. We find that pro-social subjects are likely to donate lower amounts (conditional on deciding to give and controlling for other covariates), which may be an artefact of the lab environment. But they are also more responsive to audiovisual messages on the anthropogenic cause of endangerment and show heterogeneous impacts regarding spillover effects on WTD time. We also cannot entirely rule out the potential effect of experimenter demand on behaviour. Future work can address these concerns, by using a field experiment, to test how robust these findings are in a larger and more representative sample. We also hope that subsequent research may shed further light into underlying mechanisms and processes associated with the enduring spillover effects on a broader range of behaviours, to leverage the widespread use of digital and online media, for conservation and environmental protection.

Bibliography

Alpízar, F., Nordén, A., Pfaff, A., and Robalino, J. (2017a). Spillovers from targeting of incentives: Exploring responses to being excluded. *Journal of Economic Psychology*, 59:87–98.

Alpízar, F., Nordén, A., Pfaff, A., and Robalino, J. (2017b). Unintended effects of targeting an environmental rebate. *Environmental and Resource Economics*, 67(1):181–202.

Andrade, E. B. and Ariely, D. (2009). The enduring impact of transient emotions on decision making. *Organizational Behavior and Human Decision Processes*, 109(1):1–8.

Arendt, F. and Matthes, J. (2016). Nature documentaries, connectedness to nature, and pro-environmental behavior. *Environmental Communication*, 10(4):453–472.

Baca-Motes, K., Brown, A., Gneezy, A., Keenan, E. A., and Nelson, L. D. (2012). Commitment and behavior change: Evidence from the field. *Journal of Consumer Research*, 39(5):1070–1084.

Bahk, C. M. (2010). Environmental education through narrative films: Impact of medicine man on attitudes toward forest preservation. *The Journal of Environmental Education*, 42(1):1–13.

Balmford, A., Manica, A., Airey, L., Birkin, L., Oliver, A., and Schleicher, J. (2004). Hollywood, climate change, and the public. *Science*, 305(5691):1713–1713.

Bauer, T. K., Bredtmann, J., and Schmidt, C. M. (2013). Time vs. money—the supply of voluntary labor and charitable donations across europe. *European Journal of Political Economy*, 32:80–94.

Bem, D. J. (1972). Constructing cross-situational consistencies in behavior: Some thoughts on alker's critique of mischel. *Journal of Personality*, 40(1):17–26.

Blanken, I., van de Ven, N., and Zeelenberg, M. (2015). A meta-analytic review of moral licensing. *Personality and Social Psychology Bulletin*, 41(4):540–558.

Bolderdijk, J. W., Steg, L., Geller, E. S., Lehman, P., and Postmes, T. (2013). Comparing the effectiveness of monetary versus moral motives in environmental campaigning. *Nature Climate Change*, 3(4):413.

Brañas-Garza, P., Bucheli, M., Espinosa, M. P., and García-Muñoz, T. (2013). Moral cleansing and moral licenses: experimental evidence. *Economics & Philosophy*, 29(2):199–212.

Brown, T. C., Nannini, D., Gorter, R. B., Bell, P. A., and Peterson, G. L. (2002). Judged seriousness of environmental losses: reliability and cause of loss. *Ecological Economics*, 42(3):479–491.

Bulte, E., Gerking, S., List, J. A., and De Zeeuw, A. (2005). The effect of varying the causes of environmental problems on stated wtp values: evidence from a field study. *Journal of Environmental Economics and Management*, 49(2):330–342.

Camerer, C. F. (2003). *Behavioral game theory: Experiments in strategic interaction*. Princeton University Press.

Carlsson, F., Johansson-Stenman, O., and Nam, P. K. (2014). Social preferences are stable over long periods of time. *Journal of Public Economics*, 117:104–114.

Carpenter, J. and Myers, C. K. (2010). Why volunteer? evidence on the role of altruism, image, and incentives. *Journal of Public Economics*, 94(11-12):911–920.

Charness, G., Gneezy, U., and Halladay, B. (2016). Experimental methods: Pay one or pay all. *Journal of Economic Behavior & Organization*, 131:141–150.

Clot, S., Grolleau, G., and Ibanez, L. (2016). Do good deeds make bad people? *European Journal of Law and Economics*, 42(3):491–513.

Cragg, J. G. (1971). Some statistical models for limited dependent variables with application to the demand for durable goods. *Econometrica: Journal of the Econometric Society*, pages 829–844.

DellaVigna, S. and La Ferrara, E. (2015). Economic and social impacts of the media. In *Handbook of media economics*, volume 1, pages 723–768. Elsevier.

Dirzo, R., Young, H. S., Galetti, M., Ceballos, G., Isaac, N. J., and Collen, B. (2014). Defaunation in the anthropocene. *science*, 345(6195):401–406.

Djebbari, H. and Smith, J. (2008). Heterogeneous impacts in progresa. *Journal of Econometrics*, 145(1-2):64–80.

Dolan, P. and Galizzi, M. M. (2015). Like ripples on a pond: Behavioral spillovers and their implications for research and policy. *Journal of Economic Psychology*, 47:1–16.

Doulton, H. and Brown, K. (2009). Ten years to prevent catastrophe?: Discourses of climate change and international development in the uk press. *Global Environmental Change*, 19(2):191–202.

Drews, S. and Van den Bergh, J. C. (2016). What explains public support for climate policies? a review of empirical and experimental studies. *Climate Policy*, 16(7):855–876.

Duncan, B. (1999). Modeling charitable contributions of time and money. *Journal of Public Economics*, 72(2):213–242.

d'Adda, G., Capraro, V., and Tavoni, M. (2017). Push, don't nudge: Behavioral spillovers and policy instruments. *Economics Letters*, 154:92–95.

Eckel, C. C. and Grossman, P. J. (1996). Altruism in anonymous dictator games. *Games and economic behavior*, 16(2):181–191.

Effron, D. A. and Monin, B. (2010). Letting people off the hook: When do good deeds excuse transgressions? *Personality and Social Psychology Bulletin*, 36(12):1618–1634.

Engel, C. (2011). Dictator games: A meta study. *Experimental Economics*, 14(4):583–610.

Feldman, L., Maibach, E. W., Roser-Renouf, C., and Leiserowitz, A. (2012). Climate on cable: The nature and impact of global warming coverage on fox news, cnn, and msnbc. *The International Journal of Press/Politics*, 17(1):3–31.

Ferraro, P. J. and Miranda, J. J. (2013). Heterogeneous treatment effects and mechanisms in information-based environmental policies: Evidence from a large-scale field experiment. *Resource and Energy Economics*, 35(3):356–379.

Fischer, A., Kereži, V., Arroyo, B., Mateos-Delibes, M., Tadie, D., Lowassa, A., Krange, O., and Skogen, K. (2013). (de) legitimising hunting–discourses over the morality of hunting in europe and eastern africa. *Land Use Policy*, 32:261–270.

Fishbach, A., Dhar, R., and Zhang, Y. (2006). Subgoals as substitutes or complements: The role of goal accessibility. *Journal of personality and social psychology*, 91(2):232.

Gatersleben, B., Steg, L., and Vlek, C. (2002). Measurement and determinants of environmentally significant consumer behavior. *Environment and behavior*, 34(3):335–362.

Gavin, N. T. and Marshall, T. (2011). Mediated climate change in britain: Scepticism on the web and on television around copenhagen. *Global Environmental Change*, 21(3):1035–1044.

Greitemeyer, T. (2013). Beware of climate change skeptic films. *Journal of environmental Psychology*, 35:105–109.

Gross, J. J. and Levenson, R. W. (1995). Emotion elicitation using films. *Cognition & emotion*, 9(1):87–108.

Hanley, N., Boyce, C., Czajkowski, M., Tucker, S., Noussair, C., and Townsend, M. (2017). Sad or happy? the effects of emotions on stated preferences for environmental goods. *Environmental and Resource Economics*, 68(4):821–846.

Harlé, K. M. and Sanfey, A. G. (2007). Incidental sadness biases social economic decisions in the ultimatum game. *Emotion*, 7(4):876.

Harrison, G. W. (2006). Hypothetical bias over uncertain outcomes. *Using experimental methods in environmental and resource economics*, pages 41–69.

Hart, P. S. and Leiserowitz, A. A. (2009). Finding the teachable moment: An analysis of information-seeking behavior on global warming related websites during the release of the day after tomorrow. *Environmental Communication*, 3(3):355–366.

Heckman, J., Heinrich, C., and Smith, J. (2002). The performance of performance standards. *The Journal of Human Resources*, 37.

Heckman, J. J., Smith, J., and Clements, N. (1997). Making the most out of programme evaluations and social experiments: Accounting for heterogeneity in programme impacts. *The Review of Economic Studies*, 64(4):487–535.

Howell, R. A. (2011). Lights, camera... action? altered attitudes and behaviour in response to the climate change film the age of stupid. *Global Environmental Change*, 21(1):177–187.

Howell, R. A. (2014). Investigating the long-term impacts of climate change communications on individuals' attitudes and behavior. *Environment and Behavior*, 46(1):70–101.

IUCN (2016). Red list of threatened species. http://www.iucnredlist.org/photos/2016 [Accessed: October 2016].

Jacobsen, G. D. (2011). The al gore effect: an inconvenient truth and voluntary carbon offsets. *Journal of Environmental Economics and Management*, 61(1):67–78.

Janpol, H. L. and Dilts, R. (2016). Does viewing documentary films affect environmental perceptions and behaviors? *Applied Environmental Education & Communication*, 15(1):90–98.

Kahneman, D., Ritov, I., Jacowitz, K. E., and Grant, P. (1993). Stated willingness to pay for public goods: A psychological perspective. *Psychological science*, 4(5):310–315.

La Ferrara, E. (2016). Mass media and social change: Can we use television to fight poverty? *Journal of the European Economic Association*, 14(4):791–827.

Lanzini, P. and Thøgersen, J. (2014). Behavioural spillover in the environmental domain: an intervention study. *Journal of Environmental Psychology*, 40:381–390.

Lazear, E. P., Malmendier, U., and Weber, R. A. (2012). Sorting in experiments with application to social preferences. *American Economic Journal: Applied Economics*, 4(1):136–63.

Leiserowitz, A. A. (2004). Day after tomorrow: study of climate change risk perception. *Environment: Science and Policy for Sustainable Development*, 46(9):22–39.

Lerner, J. S., Small, D. A., and Loewenstein, G. (2004). Heart strings and purse strings: Carryover effects of emotions on economic decisions. *Psychological science*, 15(5):337–341.

Lönnqvist, J.-E., Verkasalo, M., and Walkowitz, G. (2011). It pays to pay–big five personality influences on co-operative behaviour in an incentivized and hypothetical prisoner's dilemma game. *Personality and Individual Differences*, 50(2):300–304.

Loomis, J. B. (2014). 2013 waea keynote address: Strategies for overcoming hypothetical bias in stated preference surveys. *Journal of Agricultural and Resource Economics*, 39(1):34–46.

Margetts, E. A. and Kashima, Y. (2017). Spillover between pro-environmental behaviours: The role of resources and perceived similarity. *Journal of Environmental Psychology*, 49:30–42.

Mazar, N. and Zhong, C.-B. (2010). Do green products make us better people? *Psychological science*, 21(4):494–498.

Moyer-Gusé, E. (2008). Toward a theory of entertainment persuasion: Explaining the persuasive effects of entertainment-education messages. *Communication Theory*, 18(3):407–425.

Nash, N., Whitmarsh, L., Capstick, S., Hargreaves, T., Poortinga, W., Thomas, G., Sautkina, E., and Xenias, D. (2017). Climate-relevant behavioural spillover and the potential contribution of social practice theory.

Nicholson-Cole, S. A. (2005). Representing climate change futures: a critique on the use of images for visual communication. *Computers, environment and urban systems*, 29(3):255–273.

Noblet, C. L. and McCoy, S. K. (2017). Does one good turn deserve another? evidence of domain-specific licensing in energy behavior. *Environment and Behavior*, page 0013916517718022.

Nolan, J. M. (2010). "an inconvenient truth" increases knowledge, concern, and willingness to reduce greenhouse gases. *Environment and Behavior*, 42(5):643–658.

Painter, J., Kristiansen, S., and Schäfer, M. S. (2018). How 'digital-born'media cover climate change in comparison to legacy media: A case study of the cop 21 summit in paris. *Global Environmental Change*, 48:1–10.

Pergams, O. R. and Zaradic, P. A. (2006). Is love of nature in the us becoming love of electronic media? 16-year downtrend in national park visits explained by watching movies, playing video games, internet use, and oil prices. *Journal of Environmental Management*, 80(4):387–393.

Pergams, O. R. and Zaradic, P. A. (2008). Evidence for a fundamental and pervasive shift away from nature-based recreation. *Proceedings of the National Academy of Sciences*, 105(7):2295–2300.

Pooley, J. A. and o'Connor, M. (2000). Environmental education and attitudes: Emotions and beliefs are what is needed. *Environment and behavior*, 32(5):711–723.

Poortinga, W., Whitmarsh, L., and Suffolk, C. (2013). The introduction of a single-use carrier bag charge in wales: Attitude change and behavioural spillover effects. *Journal of Environmental Psychology*, 36:240–247.

Reusswig, F. (2004). *Double Impact: the climate blockbuster'The Day After Tomorrow'and its impact on the German cinema public.* PIK, Potsdam Institute for Climate Impact Research.

Sachdeva, S., Iliev, R., and Medin, D. L. (2009). Sinning saints and saintly sinners: The paradox of moral self-regulation. *Psychological science*, 20(4):523–528.

Sakellari, M. (2015). Cinematic climate change, a promising perspective on climate change communication. *Public Understanding of Science*, 24(7):827–841.

Schmidt, A., Ivanova, A., and Schäfer, M. S. (2013). Media attention for climate change around the world: A comparative analysis of newspaper coverage in 27 countries. *Global Environmental Change*, 23(5):1233–1248.

St John, F. A., Edwards-Jones, G., and Jones, J. P. (2011). Conservation and human behaviour: lessons from social psychology. *Wildlife Research*, 37(8):658–667.

Stamm, K. R., Clark, F., and Eblacas, P. R. (2000). Mass communication and public understanding of environmental problems: the case of global warming. *Public understanding of science*, 9(3):219–238.

Steg, L., Dreijerink, L., and Abrahamse, W. (2006). Why are energy policies acceptable and effective? *Environment and behavior*, 38(1):92–111.

Thøgersen, J. (2004). A cognitive dissonance interpretation of consistencies and inconsistencies in environmentally responsible behavior. *Journal of Environmental Psychology*, 24(1):93–103.

Thøgersen, J. and Ölander, F. (2003). Spillover of environment-friendly consumer behaviour. *Journal of environmental psychology*, 23(3):225–236.

Thomas, G. O., Poortinga, W., and Sautkina, E. (2016). The welsh single-use carrier bag charge and behavioural spillover. *Journal of Environmental Psychology*, 47:126–135.

Truelove, H. B., Carrico, A. R., Weber, E. U., Raimi, K. T., and Vandenbergh, M. P. (2014). Positive and negative spillover of pro-environmental behavior: An integrative review and theoretical framework. *Global Environmental Change*, 29:127–138.

van der Linden, S. (2015). The conspiracy-effect: Exposure to conspiracy theories (about global warming) decreases pro-social behavior and science acceptance. *Personality and Individual Differences*, 87:171–173.

Van der Werff, E., Steg, L., and Keizer, K. (2013). It is a moral issue: The relationship between environmental self-identity, obligation-based intrinsic motivation and pro-environmental behaviour. *Global environmental change*, 23(5):1258–1265.

Vasi, I. B., Walker, E. T., Johnson, J. S., and Tan, H. F. (2015). "no fracking way!" documentary film, discursive opportunity, and local opposition against hydraulic fracturing in the united states, 2010 to 2013. *American Sociological Review*, 80(5):934–959.

Volk, S., Thöni, C., and Ruigrok, W. (2012). Temporal stability and psychological foundations of cooperation preferences. *Journal of Economic Behavior & Organization*, 81(2):664–676.

Waters, C. N., Zalasiewicz, J., Summerhayes, C., Barnosky, A. D., Poirier, C., Gałuszka, A., Cearreta, A., Edgeworth, M., Ellis, E. C., Ellis, M., et al. (2016). The anthropocene is functionally and stratigraphically distinct from the holocene. *Science*, 351(6269):aad2622.

Waters, R. D. and Jones, P. M. (2011). Using video to build an organization's identity and brand: A content analysis of nonprofit organizations' youtube videos. *Journal of Nonprofit & Public Sector Marketing*, 23(3):248–268.

Whitmarsh, L. and O'Neill, S. (2010). Green identity, green living? the role of pro-environmental self-identity in determining consistency across diverse pro-environmental behaviours. *Journal of Environmental Psychology*, 30(3):305–314.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data.* MIT press.

3.6 Tables and Figures

Table 3.1: Conceptual framework and experimental design

Panel A: Description of variables			
	Behaviour 1	Behaviour 2	Behaviour 3
Outcomes:	Donations (Don)	Willingness to Pay Tax (WTP)	Willingness to Donate Time (WTD)
Intervention focus	Target	Non-target	Non-target
Elicitation order	First	Second	Third
Range	£0-25	0-100 pence	0-7 hours
Unit	Money	Money	Time
Measure	Revealed behaviour	Stated intention	Stated intention
Type	Voluntary contribution	Coercive regulation	Voluntary contribution
Panel B: Experimental design			
Outcomes:	Donations (Don)	Willingness to Pay Tax (WTP)	Willingness to Donate Time (WTD)
Interventions:			
Control	-	WTP No Video	WTD No Video
Intervention 1, Video	Don Control Video	WTP Control Video-D	WTD Control Video-D,WTP
Intervention 2, Cause Video	Don Cause Video	WTP Cause Video-D	WTD Cause Video-D,WTP

Figure 3.1: Charitable donations

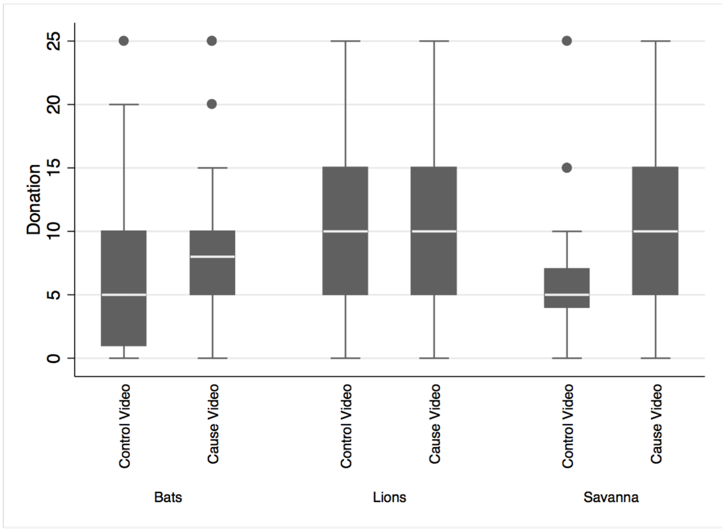


Table 3.2: Direct effect on donations: Media content on anthropogenic cause of endangerment

Sample:	All		Sub-group analysis	
Hurdle type:	Probability	Amount	Probability	Amount
Hurdle models:	(1)	(2)	(3)	(4)
Media Content = 1, Cause Video	0.234	3.073**	0.0255	-2.325
	-0.221	-1.487	-0.574	-2.974
Past Donor = 1, Yes			-0.413	-5.929**
			-0.406	-2.572
Cause Video X Past donor			0.247	7.363**
			-0.641	-3.366
Constant	7.189***	2.114	7.806***	8.391*
	-0.29	-4.007	-0.549	-4.867
Observations	223	223	223	223
Session controls	Yes	Yes	Yes	Yes
Video controls	Yes	Yes	Yes	Yes

Notes: Robust standard errors clustered at subject-level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Linear Cragg-Hurdle model with donations is truncated at 0: the hurdle is modelled as a probit regression model, and the amount donated as a truncated linear regression. Session controls include subjects per session and session dummies. Video controls includes dummies for video type (i.e., Bats, Lions and Savanna videos).

Figure 3.2: Willingness to pay (WTP) a green fee

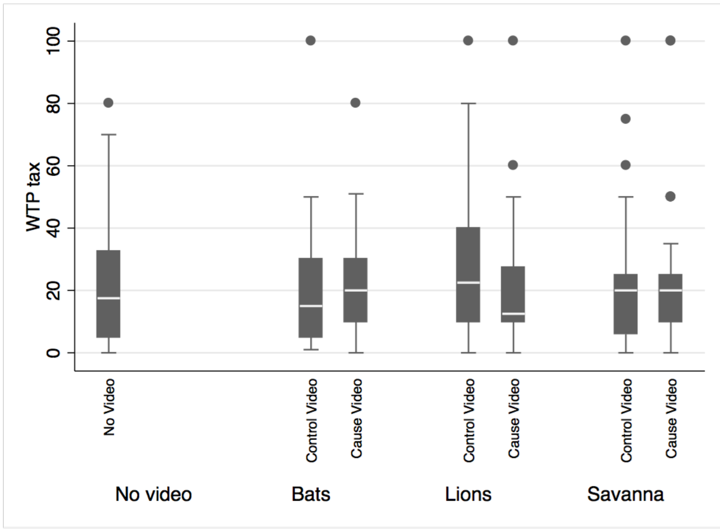


Figure 3.3: Willingness to Donate (WTD) time

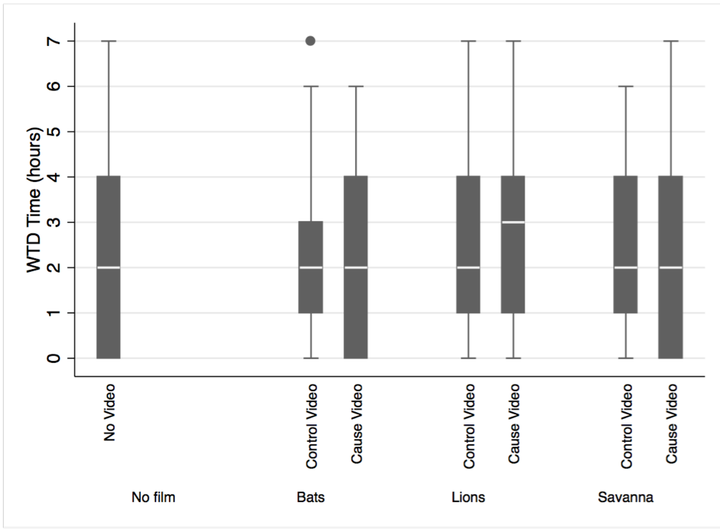


Table 3.3: Spillover effects on WTP a green fee and WTD time: Treatment effect of media exposure and media content

Treatment effect:	Media exposure				Media content on Cause			
Outcome variable:	WTP		WTD		WTP		WTD	
Hurdle type:	Probability	Amount	Probability	Amount	Probability	Amount	Probability	Amount
Hurdle model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Media = 1, Control Video	4.744***	96.46*	0.687	1.085				
	-0.601	-54.25	-0.681	-1.005				
Media = 2, Cause Video	4.836***	94.86*	0.454	1.51	0.0926	-1.72	-0.233	0.434
	-0.622	-54.28	-0.69	-1.032	-0.258	-13.05	-0.193	-0.325
Constant	-4.944	-538.7*	-1.801	-14.25**	6.274***	-60.56	0.346	1.427***
	-5.294	-307.1	-3.971	-6.157	-0.457	-79.61	-1.12	-0.494
Observations	259	259	259	259	223	223	223	223
Session controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Video controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors clustered at subject-level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Linear Cragg-Hurdle model with donations is truncated at 0: the hurdle is modeled as a probit regression model, and the amount donated as a truncated linear regression. In Models (1)-(4), No Video is the omitted category, and in Models (5)-(8), Control Video is the omitted category. Session controls include subjects per session and session dummies. Video controls include dummies for video type (i.e., bats, lions and savanna videos).

Table 3.4: Heterogeneous spillover effects: Pro-social subjects

Treatment effect:	Media exposure				Media content on Cause			
Outcome variable:	WTP		WTD		WTP		WTD	
Hurdle type:	Probability	Amount	Probability	Amount	Probability	Amount	Probability	Amount
Hurdle models:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Media = 1, Control Video	5.475***	96.45*	0.691	1.184				
	-0.769	-52.5	-0.795	-1.094				
Media = 2, Cause Video	5.071***	75.43	0.0805	-0.242	-0.404	-22.73	-0.61	-1.460**
	-0.684	-51.71	-0.799	-1.187	-0.523	-26.11	-0.43	-0.714
Past Donor = 1, Yes	0.611	22.63	-0.123	-0.932	-0.0198	14.54	-0.147	-0.939*
	-0.562	-26.15	-0.485	-0.827	-0.514	-19.86	-0.354	-0.534
Control Video X Past Donor	-0.631	-9.082	-0.0243	0.0151				
	-0.762	-31.22	-0.601	-0.984				
Cause Video X Past Donor	0.156	15.46	0.48	2.429**	0.788	26.52	0.504	2.472***
	-0.698	-33.21	-0.585	-1.005	-0.642	-31.76	-0.493	-0.83
Constant	-6.2	-526.7*	-1.665	-14.05**	5.984***	-75.29	0.463	2.071***
	-4.866	-288.2	-3.946	-5.776	-0.785	-77.18	-1.157	-0.658
Observations	259	259	259	259	223	223	223	223
Session controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Video controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors clustered at subject-level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Linear Cragg-Hurdle model with donations is truncated at 0: the hurdle is modelled as a probit regression model, and the amount donated as a truncated linear regression. In Models (1) to (4), No Video is the omitted category, and in Models (5) to (8), Control Video is the omitted category. Session controls include subjects per session and session fixed effects. Video controls include dummies for video type (i.e., bats, lions and savanna videos).

Chapter 4

Taking ‘measured’ risks while cycling: Field evidence on risk-taking and air pollution avoidance

4.1 Introduction

This paper aims to map the empirical relationship between risk preferences and daily transport behaviour in two domains: risk-taking and self-protection from air pollution while cycling. It reports the results from a lab-in-the-field experiment in a pool of 181 cyclists who attended a large cycling festival in London. The primary aim is to assess the behavioural validity of risk preference measures: to what extent do risk preference measures elicited using different methods associate with behaviour across individuals? The second aim is to explore cross-context validity: to what extent do these different risk preference measures associate with each other within an individual?

This research was motivated by the need to test different measures of risk preferences in environmental and health settings. Risk preference is widely considered a fundamental driver of behaviour. However, a closer look reveals mixed and inconclusive empirical results on the associations between risk aversion and behaviour in domains as diverse as smoking, transport, the adoption of agricultural technologies, and medical screening. Underlying these divergent results is the fact that existing studies employ multiple types of risk preferences measures, each with a distinct underlying methodological and theoretical framework.[1] For instance, current methods to measure risk preferences for health outcomes mainly rely on stated measures using self-assessments using Likert-scale questions or hypothetical scenarios. On the other hand, incentive-compatible experimental methods to measure revealed risk preferences with real consequences are commonly based on monetary outcomes. To date, there is no consensus about the 'gold-standard measurement methodology' (Galizzi et al., 2017).

A related challenge is that there is growing evidence that risk preferences are domain-specific and can even vary across different decision contexts within the same behavioural domain (Blais and Weber, 2006; Barseghyan et al., 2018). The simultaneous existence of heterogeneous risk preferences across behavioural domains and decision contexts - but within an individual - has methodological and conceptual implications. Domain-specific risk preferences are more likely to show stronger associations with behaviour and thus show stronger behaviourally validity, compared to domain-general risk preferences (Galizzi et al., 2016b; Ioannou and Sadeh, 2016). It also complicates the proposition that risk preferences are a stable personality trait (Hanoch et al., 2006). A means to address this concern empirically is to check if risk preference measures are correlated across different domains. Indeed, disagreements on how to measure risk preferences run parallel to those on the theorisation of risk aversion (Frey et al., 2017). Thus, to enhance our understanding of human choice under uncertainty, the choice of risk preference measure,

[1]See Charness et al. (2013) for a recent review.

its methodology and the behavioural domain all matter.

Few studies examine these questions in the transport domain, especially amongst active travellers in urban settings. Yet they are of interest for both research and policy. Cycling is pro-environmental and health behaviour that has been actively encouraged by policy-makers at the intersection of environmental, health and urban policy. It confers health and well-being benefits from increased physical activity, and societal benefits through reduced traffic-related emissions and burden on public transit systems (Woodcock et al., 2014). However, UK cyclists have a higher risk of death or serious injury, per mile, than users of motorised modes of transport except for motorcycles (DFT, 2015). If proximate to exhaust-emitting cars and lorries, they are exposed to higher levels of pollutants and tend to inhale more particulates because they breathe more heavily. Both risk-taking while cycling, and air pollution health risks take-away from the benefits of cycling and are barriers to increasing cycling take-up. Relatively little is known about the cyclist's preferences and behaviours (Handy et al., 2014). This knowledge is critical to design more effective policy like targeted training programs and communication interventions.[2] Furthermore, insights on the behavioural and cross-context validity of risk preferences add to methodological debates on how best to measure risk preferences in the field. Advancing this debate is the key to understanding decision-making in the environment, health and transport domains.[3]

This study jointly explored risk-taking and self-protection via air pollution avoidance.[4] Data on decision making across decision contexts within each domain were collected to explore how different risk measures associated with both aggregated behavioural outcomes for each domain, and discrete choices across contexts within domains. Three types of commonly used risk preference measures were elicited: the ordered lottery selection task (modified from Binswanger (1980, 1981) and Eckel and Grossman (2002, 2008), henceforth called BEG risk) and self-assessments on the willingness to take risk in general and health domains (from the German Socio-Economic Panel survey, hereafter called SOEP-G and SOEP-H for the domain-general risk measure and health domain-specific risk measures respectively). Besides this, precautionary attitudes towards items in a cycling kit

[2]Aldred et al. (2016) notes that take-up in the UK has not increased sufficiently despite an increase in resource allocation towards cycling. These policy learnings can be useful in other countries as well, as the number of cyclists has been rising in major cities worldwide (Pucher et al., 2011; Handy et al., 2014; Fishman, 2016).

[3]Another core dimension of the validity of risk preferences is the temporal stability of risk preferences, i.e., the stability of preferences across time for an individual elicited using different measures. See Galizzi et al. (2016a) and Chuang and Schechter (2015) for a brief review.

[4]Ehrlich and Becker (1972) differentiated between self-protection (choices that reduce the probability of a loss) from self-insurance (choices that reduce the size of a loss). Many daily decisions, such as wearing a helmet or a facemask, can be seen as self-protection, even if they can also incorporate an element of self-insurance (Gollier et al., 2013).

(e.g. Lights, Helmets and Facemasks) were measured to offer an alternate perspective of risk attitudes across different contexts within each behavioural domain. Air pollution risk perception was also measured, to investigate if subjective risk beliefs correlate with behaviour and other risk measures. To the best of my knowledge, this study is the first to elicit risk preferences using both incentive-compatible and questionnaire methods to look at risk-taking and air pollution avoidance amongst active travellers in a field setting. Turning the spotlight on air pollution avoidance is particularly novel, and overall this study is one of the few analyses that account for a variety of risk preference measures and subjective risk perceptions in a single study.

The overall finding is domain-specific risk preferences show stronger associations with risk-taking behaviour, but that risk preference measures do not associate with air pollution avoidance. More precisely, the first result of the paper is that SOEP-H, which captures an individual's self-reported willingness to take risks in health is strongly correlated with risk-taking while cycling, in particular, the aggregated outcome measure. The second result is that air pollution risk perception was strongly associated with air pollution avoidance, but none of the risk preferences measures were. Third, the different risk preference measures correlate and map onto each other, but their associations are imperfect and weak.

These results support the idea that individuals exhibit variability between different risk elicitation methods. Taking this idea further, risk preferences elicited using context-specific tasks need not predict behaviour in other contexts. This implies that future researchers need to use risk measures that are lie close to the behavioural domain under study, and measure a more comprehensive set of both risk preference and behavioural outcome measures to detect underlying behavioural tendencies. These results also suggest that risk perception – rather than risk preference – is an important explanatory variable when it comes to self-protection from ambient environmental risks like air pollution. Risk perception is arguably more amenable to change in the short-run relative to risk preferences, and therefore this finding presents a potential avenue through which policy-makers could change behaviour (discussed in section 4.5 in greater detail).

The rest of the paper is organised as follows. The next section briefly reviews different risk elicitation methods and the literature on the behavioural and cross-context validity of different risk preferences. Section three outlines the experimental method, variables and empirical model used the analysis. The next section presents the results and briefly discusses the study limitations. Section four concludes, by summarising the main findings and implications for policy and future research.

4.2 Related literature

4.2.1 Brief overview of risk elicitation methods

As an important component of the paper is to test different risk preference measures in the field setting, I briefly make a note of the main methods employed that are directly relevant to the current study. I refer the reader to Galizzi et al. (2017), Barseghyan et al. (2018), Chuang and Schechter (2015), Charness et al. (2013), Harrison and Rutström (2008), and Cox and Harrison (2008) for more detailed reviews.

Risk preferences are mostly commonly elicited in the lab and field through either experimental and questionnaire methods. Experimental methods rely on revealed behaviour and use incentive-compatible choice tasks with financial trade-offs. These trade-offs can be across investment options (e.g. in Gneezy and Potters (1997) or the GP investment game), ordered lotteries (e.g. the Multiple Price List method from Holt and Laury (2002) (HL-MPL); or the BEG risk task) or the Deal or No Deal game (DOND) (Post et al., 2008; Deck et al., 2008). Some other experimental risk measures include the Becker-DeGroot-Marshak mechanism (e.g. in Isaac and James (2000)), the Bomb Risk Elicitation Task (Crosetto and Filippin, 2013) (BRET) and the Balloon Analogue Risk Task (BART) (Lejuez et al., 2002).

Alternately, questionnaires methods rely on self-assessment measures from surveys on an individual's willingness to take risks. The German SOEP panel survey asks questions on the willingness to take risks in more generally in life (previously referred to as the SOEP-G), as well as in behavioural domains like health (SOEP-H) (e.g. in Dohmen et al. (2011)). The Domain-Specific Risk-Taking scale (DOSPERT scale) measures risk-taking in general life domain (DOSPERT-G), as well as financial, ethical, recreational, health/safety and social life domains (Weber et al., 2002). Unlike the other measures, it distinguishes between conventional risk attitudes using a risk behaviour scale and perceived risk perception.

Each method has its advantages and disadvantages. For instance, one concern is that non-incentive compatible methods are subject to hypothetical bias. Another concern is that survey questions either infer risk attitudes from self-reported engagement in risky behaviours rather than actual risk attitudes (e.g. DOSPERT) and cannot scale to a theoretically rooted risk parameter (e.g. SOEP measures). That said, designing choice tasks with real consequences across domains (e.g. for health or recreation) can be challenging, and current incentive-compatible measure predominantly rely on monetary rewards, which in turn are costly - especially if high stakes are required to dampen hypothetical bias.

4.2.2 Behavioural validity

In Expected Utility Theory (EUT), the standard economic model of decision making under uncertainty, risk aversion is conceptualised as a preference parameter and is equivalent to the concavity of the utility function (Pratt, 1964; Arrow, 1965, 1968). It is often seen as a personality trait or stable risk attitude (e.g. in Borghans et al. (2008); Becker et al. (2012)). Under this framework, one would expect risk averters are less likely to engage in risk-taking behaviour. Correspondingly, risk averters may also be more likely to engage in self-protection behaviours, which are fundamental to coping with health risks. [5]

Subsequent conceptual models suggest the relationship between risk aversion and self-protection is ambiguous (Dionne and Eeckhoudt, 1985; Briys et al., 1991; Eeckhoudt and Gollier, 2005). Dionne and Eeckhoudt (1985) showed that risk aversion need not be monotonically related to self-protection, as self-protection effort can decrease the final wealth in the state. Briys et al. (1991) shows that the relationship is ambiguous when the effectiveness of self-protection is uncertain. Eeckhoudt and Gollier (2005) show self-protection is affected by higher-order preferences, such as prudence, apart from risk aversion. They showed that prudent risk averters might have lower levels of self-protection, as prudent individuals may prefer to save effort or spending on self-protection to cover the loss if it occurs. Thus, based on theoretical models, we may expect risk aversion to be negatively associated with risk-taking, but not necessarily with self-protection.

However, results from empirical investigations are inconclusive. Studies that examine transport-related outcomes or health behaviour show positive, null, and negative correlations. For example, Anderson and Mellor (2008) obtained incentive-compatible risk preferences using the HL-MPL task from Holt and Laury (2002). They found risk-aversion was positively (albeit weakly at the 10% level) associated with higher reported seat-belt use amongst a large sample of over 900 American students and adults, but no association with driving over the speed limit. They also found weak associations with smoking, heavy drinking, and being overweight/obese. Rustichini et al. (2016) also used an incentive-compatible lottery task to elicit risk preferences amongst a sample of over 700 trainee truckers. They found no significant relationship with the number of accidents,

[5] Subsequent models in behavioural economics consider risk-taking behaviour to be an outcome of broader cognitive processes. For instance, by evaluating potential values of the gains and losses in prospect theory and by using heuristics (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992; Mousavi and Gigerenzer, 2014). Starmer (2000); Gollier et al. (2013); Mishra (2014) provide reviews on theoretical developments in economics and psychology on decision making under uncertainty.

Body Mass Index and job attachment outcomes like time of exit, but they found strong associations with smoking and credit scores in the expected directions. Goldzahl (2017) measured risk-aversion through the incentive-compatible BEG ordered lottery selection task amongst 178 French women. She found that more risk-averse women were less likely to get screened for breast cancer.[6] The current study aims to augment the literature on the behavioural validity of risk preferences by looking daily decision making in two different and under-studied domains: risk-taking and self-protection choices through air pollution avoidance, while cycling.

Most studies - including the ones reviewed above- use only a single measure of risk aversion to examining questions of behavioural validity. This practice is insufficient if risk preferences are domain-specific, as the evidence increasingly shows (Blais and Weber, 2006; Barseghyan et al., 2011; Einav et al., 2012; Dohmen et al., 2011; Galizzi et al., 2016a,b; Ioannou and Sadeh, 2016; Hanoch et al., 2006; Riddel, 2012). To illustrate, both Riddel (2012) and Ioannou and Sadeh (2016) found that subjects exhibit higher risk aversion in the environmental domain compared to the financial domain using both hypothetical and incentive-compatible tasks respectively. Similarly, Galizzi et al. (2016a) also find subjects are less risk averse in the financial domain, compared to the health domain.[7] Domain-specific risk preferences suggest that risk preference measures elicited through using incentive-compatible experimental methods using monetary payoffs may not capture risk-taking adequately in other domains like health or self-protection. Rather, domain-specific risk measures - either through experimental or questionnaire methods - may be more useful to explain variations in risk-taking and self-protection. Thus, the

[6] Such inconsistent results stretch to studies covering other behavioural domains as well. For example, risk aversion was found to be associated with lower acceptance of genetically modified food (Lusk and Coble, 2005), lower drug use (Blondel et al., 2007), lower body mass index (Sutter et al., 2013; Galizzi et al., 2016a), lower smoking and drinking (Anderson and Mellor, 2008; Reynolds et al., 2006; Khwaja et al., 2006; Barsky et al., 1997), higher demand for medical screening tests (Picone et al., 2004), reduced residential energy use (Volland, 2017), increased pesticide and fertilizer use amongst farmers (Liu and Huang, 2013; Verschoor et al., 2016), the late adoption Bt Cotton (Liu, 2013), the increased likelihood of relying on traditional seeds (Brick and Visser, 2015), lower probability of adopting energy efficient technologies and renovating homes (Qiu et al., 2014; Fischbacher et al., 2015). On the other hand, there are studies which found no association between risk aversion and smoking (Harrison et al., 2010; Szrek et al., 2012; Harrison et al., 2017; Galizzi et al., 2016a) or other health behaviours, like the consumption of junk food (Galizzi et al., 2016a). Verschoor et al. (2016) found no association between risk aversion and the growing of cash crops and market orientation amongst farmers. Barham et al. (2014) saw only a weak association between risk aversion and the timing of adoption of GM soy, and no association with GM corn, amongst a sample of US farmers.

[7] In the same vein, Einav et al. (2012) found that risk preferences that are elicited from subject's choices in insurance domains have more predictive power for explaining insurance choices than demographic variables (like age, income, gender, and race). It can also be noted that individuals may have different risk preferences according to how the risk reduction comes about, for example towards private reductions in risk (e.g. through self-protection) versus public reductions in risk (e.g. through public initiatives to reduce the need for self-protection). In such cases, private reductions in risk may act as substitutes or complements to public initiatives to reduce risk. While this is an interesting issue that needs further investigation, this paper focuses primarily on private actions to reduce risk.

current study builds on and extends the literature, by exploring both experimental and self-assessment measures of risk-taking in different behavioural domains link to risk-taking and air pollution avoidance behaviours. Data on sub-domain risk attitudes and beliefs, namely precautionary attitudes towards items in a cycling kit (e.g. Lights, Helmets and Facemasks) and Air pollution risk perception, is also collected to provide a more granular picture of the behavioural validity of risk preferences, as explained in the methods section in greater detail.

Additionally, many studies focus only a specific behaviour, or a narrow range of two to three key behaviours, to represent decision-making in a given behavioural domain. However, a substantial body of work has established that individuals make decisions across multiple distinct contexts within a given domain and there can be unintended spillover effects from one choice to the next (Truelove et al., 2014; Dolan and Galizzi, 2015; Nash et al., 2017). This implies that an individual can compensate risk-taking in one decision context (e.g. by not wearing a helmet) by acting as a risk averter in another (e.g. cycling more slowly). Therefore, focusing on one behaviour arguably presents an incomplete picture of decision making in a given domain, and implicitly assumes that choices in that context are representative of decision-making in the domain in question. Collecting data on a broader range of decision contexts could serve to guard against this, by yielding associations both with individual and aggregated outcome measures. This task is also essential because if risk preferences vary by decision context, it is not clear to what extent the result for previously studied behaviours can generalise to other settings. Hence, this paper improves upon previous work by measuring self-reported choices across different decision texts with each domain of risk-taking and air pollution avoidance, to present a more comprehensive picture of decision making. Specifically, it considers both discrete choices across contexts within domains and aggregated measures of behaviour for a given domain.[8]

4.2.3 Cross-context stability

Only a limited set of recent studies have explored the question of cross-context validity. One line of research uses within-subjects design with representative samples: Dohmen et al. (2011); Josef et al. (2016); Coppola (2014) consider Germany, and Galizzi et al. (2016a) study the U.K. Another line of research uses a lab-in-the-field method with non-student samples and a within-subjects design (Dave et al., 2010; Reynaud and Couture, 2012; Galizzi et al., 2016b; Riddel, 2012). Other studies use lab experiments (mostly

[8]Bradford et al. (2017) adopt a similar approach when testing for the behavioural validity of time preferences.

with students or those enrolled in experimental laboratories in universities) with either a within-subjects design (Lönnqvist et al., 2015; Deck et al., 2013; Loomes and Pogrebna, 2014; Isaac and James, 2000; Vieider et al., 2015; Falk et al., 2015; Dulleck et al., 2015; Csermely and Rabas, 2016; Attanasi et al., 2016; Berg et al., 2005; Hey et al., 2009) or a between-subjects design (Crosetto and Filippin, 2016). The evidence so far shows mixed evidence on cross-context validity. The majority of studies also rely on lab experiments, with student samples, especially when more than two risk measures are considered. [9]

For instance, Dohmen et al. (2011) tested for associations between an experimental and incentive-compatible risk measure using a multiple price list (not the HL-MPL) and the SOEP-G risk measure. They elicited risk preferences using a fixed order of questions, such that subjects went through a detailed questionnaire, which elicited the SOEP-G risk measure, immediately followed by the paid lottery experiment. They find that the SOEP-G predicts the experimental measure quite well. Galizzi et al. (2016a) tested two experimental measures (HL-MPL, BEG) and three survey measures (SOEP-G, SOEP-H and SOEP-Finance). They first measure HL-MPL (alongside time preferences), followed by BEG risk measures, after which subjects answered a standard module of the U.K. Understanding Society survey, that contained the SOEP questions. They found mixed results on cross-context validity; the HL-MPL measure was correlated with the SOEP-G, but no other survey measure and the BEG risk measure was correlated with all survey measures.

Field-based studies also show mixed evidence on cross-context validity. For instance, Dave et al. (2010) find measured risk aversion is higher when it is elicited using the HL-MPL lottery, compared to the BEG lottery, in a sample of Canadian residents (subjects completed the BEG task before attempting the HL-MPL task). Conversely, Reynaud and Couture (2012) found risk aversion measured using the BEG task is higher than when measured in the HL-MPL, in a sample of French farmers (with hypothetical lotteries). Subjects first undertake the HL-MPL task, followed by the BEG-task. They find HL-MPL and BEG risk measures are significantly correlated. They find only weak correlations between the experimental and DOSPERT measures (with DOSPERT-General, Finance and Recreation, but not with Health/Safety, Social or Ethical). Lab experiments also reveal limited support for cross-context validity. For instance, Lönnqvist et al. (2015) compare risk aversion elicited using the HL-MPL and an aggregated General Risk Factor composed of the different SOEP measures (such as social, health, finance etc.) in a within-subjects lab experiment. They find no correlation between the General Risk factor form

[9] Many studies in this literature also check for associations between economic preferences (such as time, risk, trust and altruism), to psychological traits (e.g., like the Big-5 personality traits, the locus of control, and cognitive ability).

the questionnaire and the HL-MPL risk measure (also see Crosetto and Filippin (2016)).[10]

This study extends the currently limited literature on cross-context validity in three main ways. Firstly, it extends the evidence to an under-examined sample and field setting, as well as two new behavioural domains as previously discussed. In this way, it takes the evidence on cross-context validity outside the lab and student sample, and into the field. Second, it considers a broader range of risk measures, specifically the BEG, SOEP-G and SOEP-H risk measures, and precautionary attitudes and air pollution risk perception, alongside more standard risk measures. Thirdly, it offers methodological improvements in the experimental design, as the order of the risk questions is randomised. Randomization serves to mitigate order and anchoring effects, which may affect the risk measures observed in many previous studies, and thereby the results about cross-context validity.

4.3 Experimental method

This analysis draws on data from a lab-in-the-field experiment as defined in Gneezy and Imas (2017).[11] Data was collected using an experimental survey in the public festival zones of the Prudential Ride London (PRL) Festival held during 28-31 July 2017. The experiment targets urban cyclists, who are a theoretically relevant population, especially in the context of targeted programs on risk-taking, road safety and air pollution avoidance in urban cycling. The PRL cycling events are geared towards both professional and amateur cyclists, and a random ballot determines participation held the previous year. As it is open to the public, interested spectators can attend with their families. They can also take part in numerous other cycling themed festivities in the public festival zones. This locale offers a distinctive opportunity to access cyclists of different types and abilities, including commuters, recreational cyclists, and those interested in cycling. The following subsections summarise the experimental procedure, risk and outcome measures, control variables, and empirical model used in the analysis.

[10](Barseghyan et al., 2011) infer underlying risk preferences from households insurance choices in three domains: auto collision, auto comprehensive, and home all perils, and extract their risk preferences from these choices. They test whether household's deductible choices across domains overlap over different intervals of the degree of absolute risk aversion. They find evidence to the contrary, as the three intervals intersect for only 23 percent of households.

[11]Harrison and List (2004) call this an 'artefactual field experiment', given the non-standard nature of the subject pool (i.e., non-students) and the lab-experimental protocol.

4.3.1 Procedure

The study was approved by the LSE Ethics review process. Convenience sampling was used, as surveyors were stationed at fixed locations in public festival zones and directly approached potential participants. Individuals were informed that the study looked at cycling and air pollution in London, that they could win a prize and possibly some money for their participation, and that time required varied from around 10-15 minutes. The entire survey was conducted on electronic tablets and hosted on Qualtrics survey program. Interested individuals participated upon answering three qualifying questions in the affirmative: (1) they are residents in the Greater London Area (2) they cycle in London for either recreation/commuting/both and (3) they are over 18 years of age. After the surveyor entered these responses, tablets were handed to the participant, who completed the remainder of the survey alone after agreeing to the consent form. Surveyors were available to assist with any questions from the subjects but took care to not see any responses.

At the start of the survey, subjects were directed to a preamble which requested them to read the questions carefully, answer truthfully and by themselves. The preamble aims to promote clarity about the survey protocol. After this, subjects answered the survey component on risk elicitation, followed by cycling and air pollution. Then, they were exposed to some information about air pollution and could choose a prize for the draw. The experimental survey concluded after subjects answered questions on socio-demographic attributes. After this, subjects participated in the lucky draw, which determined whether they would receive any participation prize, as well as their payout from the risk task, described below. Appendix H provides more details about the experimental survey, data collection, and variables.

4.3.2 Risk measures

The risk measures are the primary explanatory variables of interest in this study. Given the limited resources available for the study, only one incentive-compatible experimental risk measure could be investigated. Simplicity and clarity of the choice task were the overarching criteria that guided the choice of the risk elicitation methods, to mitigate the cognitive and time burden on participants and mitigate attrition. Thus, an incentive-compatible version of the BEG task was used. Compared to alternatives like the HL-MPL method, this technique is more straightforward to comprehend if subjects have heterogeneous numerical and literacy skills (Charness et al., 2013; Dave et al., 2010). Also, it is simpler to execute in the field using a standard coin toss and correlates well with self-assessment risk measures and behaviours across many contexts (Reynaud and Couture, 2012; Galizzi et al., 2016a; Crosetto and Filippin, 2016). A potential drawback is that a given gamble may serve to anchor expectations due to the gain-loss frame, which may induce individual's to take decisions based on reference dependence (Harrison and Rutström, 2008).

Subjects are presented with five lotteries characterised by a linearly increasing expected value and higher standard deviation. Each outcome in each gamble has a 50% chance of success, and subjects can select their most preferred lottery. Table 4.1 presents details of the BEG task used in this study. The same monetary payoffs used in Crosetto and Filippin (2016) are also employed here (in Great Britain Pound (£)). Assuming constant relative risk aversion (CRRA) utility and that each subject's utility function takes the form:

$$U = \frac{x^{(1-r)}}{(1-r)} \tag{4.1}$$

Here, r is obtained as the CRRA parameter. The ranges of r can be estimated from the gamble and are calculated as a function of the monetary payoff from the gamble. Risk-averse subjects should choose one of the lotteries numbered one to four. A risk-neutral or risk-seeking subject should choose lottery five, as it yields the higher expected value. This version of the BEG task cannot differentiate between risk-neutrality and risk-seeking. Another version of the BEG task in Dave et al. (2010) features an additional lottery characterised by the same expected value as the fifth lottery, but by a higher variance. As noted in Crosetto and Filippin (2016), while the additional choice allows separating the behaviour of slightly risk-averse agents from that of risk seekers, a risk-neutral agent would still be indifferent between the two. Subjects obtain the chance to play the lottery in a coin toss if they win the prize draw.

[Table 4.1]

Two self-assessment questionnaire risk measures were employed from the German Socio-Economic Panel Study, to measure the willingness to take risks in general and health domains. The question asks subjects to report from a 1 to 11 scale, 'Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?'. Here, 1 is 'Unwilling to take risk' and 11 is 'Fully prepared to take risk'. For willingness to take risks in health, subjects report on a 1 to 11 scale, 'Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks in health?. These single-item questions were picked over experimental methods to elicit subjective probabilities and DOSPERT questionnaire due to resource constraints and to reduce the time and cognitive burden on participants. Crosetto and Filippin (2016) show that the DOSPERT and the SOEP measures are strongly correlated both at the aggregated level and across DOSPERT subscales, including health. Besides, the behavioural validity of these questions has been explored in Dohmen et al. (2011), who find relatively strong correlations with different behavioural outcomes and across behavioural contexts.

To measure precautionary attitudes in the cycling domain specifically, self-assessment questions about the importance of safety-items in a cycling kit - namely lights and helmets - are asked, as both items are essential from accident prevention standpoint. In addition, we ask subjects to rate the importance of anti-pollution face-masks as a part of a cycling safety kit, to assess whether there is any relationship to avoidance behaviour. Specifically, subjects are asked 'What do you think are essential to a cycling kit?' and they report on a 1 to 5 scale, where 1 is 'Not at all important' and 5 is 'Extremely important'. This is similar to measures of safety attitudes to cycling used in other studies (Chataway et al., 2014; Lawson et al., 2013). The item order in the question (i.e., Lights, Helmet, Facemask) is randomised to mitigate order effects.

Finally, air pollution risk perception, a type of subjective risk belief, is also measured. Risk perception is consistently associated with a variety of environmental and health behaviours like the greater willingness to mitigate climate change (Leiserowitz, 2006; Spence et al., 2011, 2012), greater frequency of breast cancer screenings and the uptake of mammographies (Goldzahl, 2017; Carman and Kooreman, 2014; Katapodi et al., 2004), and decisions to purchase flood insurance policy (Petrolia et al., 2013). A single-item self-assessment question is used because it yields a parsimonious focus to examine the relationships with other indicators (Kahan et al., 2012; Ganzach et al., 2008). Subjects are asked to report on a 1 to 11 scale, 'How much risk, if at all, do you think air pollution poses to your health and safety?'. Variations of this single-item measure have been used in previous research to measure the perceived severity of other environmental risks including climate change (Kahan et al., 2012).[12]

Subjects first face the block of risk elicitation questions, after reading the preamble, namely the BEG task, SOEP-G and SOEP-H questions. Unlike many studies reviewed earlier, the order of the risk questions is randomised to mitigate ordering and anchoring effects on measured responses. The other two risk measures, namely on attitudes towards items in the cycling kit and air pollution risk perception, were asked in the survey block on cycling behaviour and air pollution respectively. Notably, the question order in each of these blocks was also randomised.

[12]See Appendix H for a short note on risk perception and its measurement methods.

4.3.3 Dependent variables: Risk-taking and air pollution avoidance

The paper explored two categories of dependent variables. First, risk-taking while cycling focuses on risky behavioural choices taken while cycling. Second, air pollution avoidance pertains to a range of preventive health choices against an ambient environmental risk factor. Within each category, self-reports of individual behavioural practices were measured, which are aggregated to form a composite behavioural measure for each domain. In this way, I attempted to quantify micro-behavioural processes that constitute decision making in both domains and aggregate these behaviours to obtain a composite outcome measure. As before, the order of behaviours displayed in each question was randomised to mitigate order effects.

To measure risk-taking while cycling, subjects were asked, 'How often, if ever, do you do any of the following?', and they report on a 1 to 5 scale, where 1 is 'Never' and 5 is 'Always'. The options were identified from previous studies of risk-taking while cycling and the pilot study, and include six behaviours: cycle through red lights (Red lights), cycle with music in headphones (Music), cycle after dark without lights (No lights), cycle using a mobile phone (Mobile), cycling without a helmet (No helmet), and cycle after drinking alcohol (Alcohol). For the composite risk-taking while cycling variable (referred to as 'Risk-taking'), the answers to the individual items are aggregated to form a minimum score of 6 (Never is selected for all six risk-taking behaviours) and a maximum score of 30 (always for all six behaviours). Thus individual risk-taking behaviours and the aggregate risk-taking variable are ordinal.

To measure air pollution avoidance while cycling, subjects were asked, 'Do you engage in the following actions to avoid air pollution?', and were provided with a list of options. The options were identified from the pilot study and the advice pages of the National Institute for Health Research (NIHR, 2017). The six options include avoiding main and busy roads (Avoiding main roads), avoiding busy and peak hour travel (Avoiding peak travel), using your bike/walk for short journeys instead of car/public transport (Biking short distances), avoiding stopping behind large diesel vehicles (Avoiding stopping behind vehicles), wearing an air-pollution face mask (Facemask), checking air pollution levels on the news, internet and/or mobile applications (Checking air pollution) and/or none of the above (None). Note that the list of avoidance behaviours included both incidental strategies, which may be taken to avoid accident risk or other environmental stressors like noise or congestion (e.g. avoiding main roads and peak travel) and deliberate strategies to unambiguously to avoid air pollution (e.g. wearing facemasks). Subjects reported whether they engage in a given avoidance behaviour or not. Thus each avoidance behaviour is a categorical variable, taking either 0 (No) or 1 (Yes). The aggregate avoidance behaviour is a count variable or the sum of all the individual behaviours and can take a minimum of 0 (None) or 6 (individual engages in all six avoidance behaviours).

4.3.4 Control variables

Additional data were collected on cycling behaviour, air pollution knowledge, and socio-economic attributes to address omitted variable bias and to control for any unexplained variance. Cycling behaviour variables were the type of cyclist (Cyclist type), i.e., recreational or commuter cyclist (Com), or both (Rec+Com)commuter cyclists and frequency of cycling (Cycle freq.).

To measure air pollution knowledge, which has been flagged as a significant predictor of risk perception (Kahan et al., 2012; Leiserowitz, 2006), subjects were asked standard questions to assess how much they know about the sources of air pollution. The responses were aggregated to form an air pollution knowledge score (AP knowledge).

Finally, the models control for socio-demographic attributes including age, gender, ethnicity, income and education level. The empirical evidence about how these attributes correlate with risk preferences is not straightforward. I illustrate this using the examples of gender and age. The conventional understanding is that that females show higher risk aversion than males (Eckel and Grossman, 2008; Holt and Laury, 2002; Croson and Gneezy, 2009; Charness and Gneezy, 2012). Studies also found older persons show greater risk aversion (Halek and Eisenhauer, 2001; Paulsen et al., 2011). However, subsequent empirical evidence muddies these trends: Nelson (2015) re-analysed 35 frequently cited studies on gender differences in risk aversion, and found that differences are not as substantial are commonly claimed because the standardized differences in means amounted to less than one standard deviation in most cases, and the degree of overlap between male and female distributions generally exceeded 80%. Similarly, Filippin and Crosetto (2016) gather data from 54 replications of the Holt and Laury (2002) risk task, to find that significant gender differences appear in less than 10% of the studies, and depend on design features (e.g. presence of a safe option; also see Harrison et al. (2007) and Schubert et al. (1999)). Other studies show that older adults are not necessarily more risk averse either (Mather et al., 2012). Nevertheless, I control for these attributes as a robustness check in the empirical analysis.

4.3.5 Payment and survey completion

The two central design decisions regarding payment were whom to pay and when to do so. Given the limited resources available, the reluctance to collect personal details of respondents and for ease of implementation in the field, it was decided that only a subset of subjects would be paid immediately after they completed the survey. Thus, after subjects completed the socio-demographic questions, they were given instructions for the prize draw. The results of the prize draw determine whether the subject gets the chance to play the BEG lottery task, and obtain the participation prize. The probability of winning the prize draw is fixed across subjects, and everyone had an equal 1-in-50 chance. A review of the literature in Charness et al. (2016) suggests that paying on a subset of players in incentive-compatible risk tasks can have no or limited impact on responses. That said, this payment feature must be kept in mind while interpreting the results.

The implementation procedure was as follows: subjects had to pick a number between 1 and 50 and tell the surveyor. They handed back the tablet to the surveyor. After this, they picked one token from a bag of tokens numbered 1-50, and if the number picked from the bag matches the number vocalised to the surveyor, the subject wins the prize draw. The outcome of the BEG task is determined by a coin toss, where subjects obtain Event A if heads are realised and Event B otherwise. If subjects win the draw, they enter their email addresses on the tablet and are contacted the following week for their chosen prize.

4.3.6 Empirical models

The primary objective of the empirical model is to test for statistically significant associations between risk preferences and the dependent variables on risk-taking and avoidance behaviours, i.e., behavioural validity of risk measures. In order to address this, the following regression model is run for each outcome:

$$y_i = \alpha + \beta r_i + \gamma X_i + \theta S_i + \varepsilon_i \tag{4.2}$$

where i denotes individuals, r_i is the risk measure in question, X is a set of control variables, β and γ are parameters to be estimated, and ε_i is the error term. Individual control variables include cyclist type, cycling frequency, air pollution knowledge, age, gender, ethnicity, income and education covariates, where the omitted categories for age is less than 35 years old, for gender is male; for ethnicity is white, for income is earning a household income of less than £32,000, and for education is those having less than undergraduate degree (UG). To control for potential survey fixed effects, S is a set of survey controls which include dummies for the surveyor, time and location of the survey.

As previously discussed, the behavioural outcomes are a mix of ordinal (individual risk-taking behaviours and aggregate risk-taking), binary (individual avoidance behaviours), and count variables (aggregate avoidance). The explanatory variables are treated as continuous variables, and the raw choice data is used. [13]

Ordered logistic models are used for the ordinal outcomes, logistic models for the binary outcomes and Poisson models for the for the count dependent variables. The reported estimates are ordered log-odds (logit) regression coefficients for the ordered and binary logistic regressions. The coefficients are the difference in the logs of expected event rate (or count of the number of events) or the log of the rate ratio for the Poisson regression models.

To test the cross-context validity of different risk measures, pairwise correlations of the raw choice data between different risk measures is first undertaken. Then, the robustness of these associations is further tested using ordered probit regressions models, with and without individual controls.

The results of the models testing behavioural and cross-context validity are summarised in the text without details of the coefficients of the individual controls for brevity. Appendix D presents results of the full specifications of all the models.

4.4 Results

4.4.1 Sample characteristics

Table 4.2 summarises the distribution of responses for each control variable used in the analysis. The final sample consists of 181 survey responses, since nine responses were omitted due to interruptions or because they were incomplete. The majority of subjects identify as both recreational and commuter cyclists (75%). The frequency of cycling is also higher in this sample: 89% reported cycling at least once a week compared to 76% in representative surveys from cyclists in London (TfL, 2016). The majority of subjects were below 55 years of age, male, white, with a reported household income of over $64,000, and at least an undergraduate degree. The over-representation of affluent, white men mirrors

[13] In future work, I plan to retrieve the CRRA parameters from the BEG task, and test associations using interval level regressions.

findings from other representative surveys and qualitative studies on cycling in London and the UK (Aldred et al., 2016; Steinbach et al., 2011; TfL, 2016).

[Table 4.2]

4.4.2 Description of risk measures

Table 4.3 provides descriptive statistics of the different measures of risk. When we consider the BEG risk measure, the mean lottery choice is 2.16 (S.D. = 1.57, median = 2), compared to an average lottery choice of 2.79 in Crosetto and Filippin (2016) (S.D. = 1.29, median = 2 or 3, n = 88 students), and 3.45 in Eckel and Grossman (2008) (S.D. = 1.17, n = 256 students). These responses imply that 77.35% of the sample is risk-averse (they choose one of the Lotteries 1 to 4), and 22.65% is risk neutral/seeking (they choose Lottery 5). This result is in line with Crosetto and Filippin (2016), who observe 20% of the sample is risk neutral/seeking. This is also similar to Galizzi et al. (2016a), who observe that nearly 24% of the subjects choose the risk-neutral/seeking option in the BEG task (albeit with different money payments), in a representative U.K. sample. When we consider the distribution of responses across gamble choices, Lottery 1, the most risk-averse option (£4 versus £4) is most popular, as it is chosen by 36.46% of the sample (similarly, Galizzi et al. (2016a) find 35.11% chose the safe lottery choice). Given this, the responses collected in the survey seem to correspond to results in previous studies. To test whether BEG preferences predict avoidance, an ordinal variable is used, and it takes value 1 for Lottery 1 and value 5 for Lottery 5.

[Table 4.3]

Next, consider responses to the SOEP-G and SOEP-H questions. The mean willingness to take risk according to the SOEP-G and SOEP-H questions are 7.05 (S.D. = 2.24) and 6.28 (S.D. = 2.52) respectively. This figure is higher than the willingness to take risk observed in other studies. For instance, the mean General risk attitude using the SOEP question is is 5.29 in Crosetto and Filippin (2016), and 4.76 in Dohmen et al. (2011) (S.D. = 2.54, n = 450 in the experiment, and mean = 4.42, S.D. = 2.38, n = 21,875 subjects in SOEP survey in Dohmen et al. (2011)). It is also higher than Galizzi et al. (2016a)'s representative U.K. sample, where mean SOEP=-G and SOEP-H values are 4.52 and 3.15 respectively. To test whether willingness to take risk predicts avoidance, SOEP-G and SOEP-H are used as decreasing measure of risk aversion, such that the minimum value of 1 denotes 'unwillingness to take risks', and the maximum value of 11 denotes 'fully prepared to take risk'.

When the responses to these standard risk measures are considered, BEG risk aligns with responses obtained in some other experiments and representative samples. However, the SOEP-G and SOEP-H measures denote lower risk aversion amongst our sample compared to other studies. One possible explanation is the self-selection of less risk-averse individuals into the cycling in London can be perceived as and is a risky activity. Suggestively, the perception that cycling in London is 'too dangerous' is the main reported reason (around 50% of those surveyed) for cycling less, primarily due to fear of traffic collisions (TfL, 2017). Along these lines, other studies have pointed out that individuals who engage in risky sports may not act less risk averse than others in economic tasks with incentives (Collard and Oboeuf, 2013; Riddel and Kolstoe, 2013). For example, Riddel and Kolstoe (2013) found that risk aversion amongst risky recreationists (e.g. amateur auto racers and SCUBA divers) are qualitatively similar to a student control group (elicited using incentive-compatible HL-MPL). More broadly, these somewhat inconsistent results seem to suggest that the experimental and survey risk methods are measuring different risk preferences.

Finally, we consider self-assessments of Air Pollution Risk Perception (APRP) and precautionary attitudes, captured through the importance of Lights, Helmets and Facemasks. The average APRP score is 7.956 (S.D. = 2.035, median = 8 or 9), and no subject reported that air pollution posed no risk (the minimum possible scores of 1 and 2 were never chosen). The APRP variable is an increasing measure of risk perception, such that the minimum value of 1 denotes 'no risk at all', and the maximum value of 11 denotes 'extreme risk'. Helmets are reported as extremely important by most subjects (58.56%), followed by Lights (35.91%). Although the majority of subjects report that face-masks are slightly or moderately important (48.07%), only 4.4% of subjects reported that face-masks were extremely important. The mean (S.D.) scores are all reported in Table 4.3. Lights, Helmet and Facemask variables are all ordinal, and denote increasing precaution, where 1 is 'not at all important' and 5 is 'extremely important'.

4.4.3 Behavioural validity I: Risk measures and risk-taking

The associations between aggregated and discrete risk-taking behaviours and risk preferences are explored to investigate behavioural validity. Figures 4.1 and 4.2 illustrate the responses to the risk-taking questions. The least common behaviour was using a mobile while cycling (72.38% reported Never), followed by listening to music and cycling (69.61% reported Never) and cycling without lights in the dark (66.85% reported Never). The most common risk behaviour was not wearing a helmet (12.71% reported Always, and 20.99% reported Sometimes). Another common risk-taking behaviour was cycling through a red light (46.96% of the sample reported Sometimes). For the aggregate variable, the mean risk-taking score was 9.56 (S.D. = 2.832, median = 8).

[Figure 4.1] and [Figure 4.2]

Tables 4.4 to 4.6 present results of the ordered logistic model's regression models for aggregate and individual risk-taking behaviours following empirical model (1) specified in section 4.3.6. Table 4.4 considers aggregate risk-taking behaviour as the outcome variable. Models with and without individual controls are presented. All regressions control for potential survey fixed effects as discussed earlier and use heteroskedasticity robust standard errors. A positive association should occur between risk measures and risk-taking behaviours (or a negative association with precautionary attitudes). It is clear that that the empirical evidence is mixed. The BEG risk measures are positively correlated with risk-taking while cycling, but the coefficient is not statistically significant. The SOEP-G risk measure is also positively associated and statistically significant at the 10% level. The SOEP-H measure, on the other hand, is positively associated and statistically significant at 1% (for example in model (6), beta = 0.214, S.E. = 0.068, p = 0.002). This finding implies that for a one unit increase in the SOEP-H score, the odds of having the highest aggregate risk-taking versus the combined lower scores is 1.234 times higher, holding other variables constant.

[Table 4.4, Table 4.5 and Table 4.6]

Moving onto the association between Lights and Helmets and risk-taking, the coefficients are negatively signed as expected, and significant at 1%. The magnitude of both these coefficients are also higher (e.g. in model (8) with Lights, beta = -0.485, S.E. = 0.147, z = -3.29, p = 0.001 and in model (10) with Helmets, beta = -0.791, S.E. = 0.134, z = -5.89 , p = 0.000). This result implies that for a one unit increase in the Lights and Helmet score, the odds of having the highest aggregate risk-taking versus the combined lower scores is 0.615 and 0.453 times lower respectively, keeping all other variables constant. When we consider the linkages between individual covariates and risk-taking behaviour (full specifications are reported in Appendix D), three main empirical results hold and is consistent with previous work. Firstly, identifying as female is negatively associated with higher risk-taking relative to males in all specifications. Secondly, those falling in higher age categories (35-54 years and over 55 years, the omitted category is 18-34 years) is negatively associated with higher risk-taking in all specifications. Thirdly, those reporting household incomes of over £64,000 also report less risk-taking compared to those earning below £32,000 in all specifications.

Turning to individual risk-taking behaviours in Table 4.5 and 4.6, we see that the picture become a bit more varied. Consider self-reports on cycling through red lights (Table 4.5, models (A1) to (A5). SOEP-H is positively correlated with the outcome (at 10% significance level), and the coefficients on Lights and Helmets remain negative and significant at 1%. However, SOEP-H is positively correlated to listening to music while cycling (at 5% significance level) and using mobile while cycling (at 1%) significance level. Indeed, the BEG risk measure is positively and significantly related only to the Mobile outcome (Table 4.5, model (D1)). As expected both the Lights and Helmet variables are strongly negatively associated with cycling without Lights and Helmet (Table 4.5, model (C4) and Table 4.5, model (E5)).

When we consider how individual covariates predict individual risk-taking behaviours the picture is more mixed (full specifications are reported in Appendix D). Firstly, identifying as female is negatively associated with Mobile (compared to males), but with no other risk-behaviour (coefficients are negative but not statistically significant). Secondly, those falling in higher age categories (35-54 years and over 55 years, the omitted category is 18-34 years) is negatively associated and statistically significant only for Mobile use and Music. Thirdly, those reporting household incomes of over £64,000 are negatively and significantly associated with No helmet, compared to those earning below £32,000 in all specifications. More broadly, these results indicate variation in risk-taking across behavioural contexts according to different socio-economic categories.

Overall these results suggest that domain-specific risk measures are more strongly associated with risk-taking while cycling, and aggregated behavioural outcomes. Aggregate risk-taking while cycling is more correlated with the domain (SOEP-H) and sub-domain specific (Lights, Helmet) risk measures rather than general risk attitudes (SOEP-G). Also, the BEG measure is not significantly associated with (aggregate) risk-taking while cycling. This provides empirical support to the idea that domain and sub-domain-specific risk measures (risk measures in health and cycling) are more strongly correlated with risk-taking behaviour. This is particularly evident from the strong correlations between risk-taking behaviours and risk measures regarding lights and helmets. These results are consistent with studies which highlight that risk preferences vary across domains and decision contexts within domains (Blais and Weber, 2006; Hanoch et al., 2006; Galizzi et al., 2016b; Barseghyan et al., 2011). It also suggests that different risk elicitation methods (i.e., experimental and questionnaire) may capture risk preferences that correspond to different behavioural contexts. Besides, these results suggest that risk measures are more strongly associated with aggregated measures in a given domain, rather than discrete behaviours across decision contexts within a domain. This is consistent with findings that individual behaviours may only be weakly correlated with measured preferences, because of the idiosyncratic effects (Bradford et al., 2017).

4.4.4 Behavioural validity II: Risk measures and air pollution avoidance

Figures 4.3 and 4.4 illustrate the responses to the air pollution avoidance questions. We see some variation both in the number and types of avoidance behaviours undertaken. While 20.44% of the subjects do not undertake any avoidance, the majority of subjects (79.56%), undertake at least one avoidance strategy. Incidental avoidance strategies are most popular, especially avoiding stopping behind vehicles (53.04%) and avoiding busy roads (41.99%). Deliberate avoidance is markedly less frequent; only around 5% of subjects report using an anti-pollution face-mask and checking air pollution levels on the news. The aggregate outcome variable of avoidance is the count of avoidance behaviours, that takes a minimum value of 0 (no avoidance) and a maximum value of 6 (an individual undertakes all 6 avoidance behaviours). The mean count is 1.734 (S.D. = 1.323), and the median and the modal number of avoidance behaviours is 2 and 1 respectively.

[Figure 4.3 and Figure 4.4]

Tables 4.7 to 4.9 present results of the regressions examining the associations between risk preferences and self-reported air pollution avoidance, for aggregate and individual behaviours. First consider Table 4.7, that presents the results on the aggregate avoidance as the dependent variable (# Air pollution avoidance), with and without individual controls. All models employ robust standard errors and survey controls. Firstly, it is clear that the standard risk measures, (BEG, SOEP-G and SOEP-H) do not predict the extent of avoidance undertaken robustly. Indeed models (1) to (4) in Table 4.7 show the expected negative association between the extent of avoidance and BEG and SOEP-G risk measures, but none of the coefficients is statistically significant. Models (5) and (6) show that SOEP-H is positively associated with the aggregate avoidance, but the relationship is not statistically significant at conventional levels. There is a positive association between precautionary attitudes towards Lights and Helmets as expected, but only the coefficient on Lights is weakly significant at the 10% level when individual controls are added (in model (8) beta = 0.091, S.E. = 0.055, z = 1.66, p = 0.097).

[Table 4.7]

The risk measures that does predict the extent of avoidance undertaken is precautionary attitudes to Facemasks and Air Pollution Risk Perception (APRP). The coefficient on Facemasks is positive and significant at the 1% level with and without individual controls (from model (12) beta = 0.191, S.E. = 0.054, z = 3.52, p = 0.000). This suggests that for a one unit increase in the Facemasks variable, the incident rate ratio of the number of avoidance behaviours increases by 1.210 times, holding all other variables constant. The coefficient on APRP is also positive and significant at the 1% level for models with and without individual controls (in model (14) beta = 0.088, S.E. = 0.030, z = 2.90, p = 0.004). This suggests that for a one unit increase in the APRP variable, the incident rate ratio of the number of avoidance behaviours increases by 1.092 times. Thus both the economic magnitude and significance of both these risk measures are similar. From Table 4.7, we also see that the coefficient on Air Pollution (AP) knowledge is positive and significant at the 1% level in all specifications. No other individual covariate is associated with aggregate avoidance in a robust manner (full specifications in Appendix D).

To consider the association between risk measures and individual avoidance strategies, we consider the four most popular avoidance behaviours namely, Avoiding main roads, Avoiding Peak travel, Avoiding stopping behind diesel vehicles and Biking short distance.[14] Tables 4.8 and 4.9 present results of the logistic models, where the coefficients are in log-odds units. The empirical picture is mixed and reiterates the limited behavioural validity of standard measures. For instance, consider models (A1) to (A7) in Table 4.8, where Avoiding busy and main roads as the binary outcome variable. There is a negative association between avoiding main roads and SOEP-G (weakly significant at 10%), suggesting those who are report greater risk seeking in life are less likely to avoid main roads. Conversely, there is a positive association between precautionary attitudes towards Lights and Facemasks and the likelihood of avoiding main roads (both significant at 5%, in models (A4) and (A6)). More generally, the coefficient on Facemasks is positive and significant at 5% for two other avoidance strategies, namely Avoiding Peak travel (model (B6) significant at the 1% level) and Stopping behind vehicles (model (C6) significant at the 5% level). Also, APRP is positively associated with the likelihood of Stopping behind vehicles (significant at 10%, model (C7)) but not other individual avoidance behaviours.

When we consider models with individual covariates, AP knowledge is positively and significantly related only to Avoiding peak travel and Biking short distances. We also observe that those earning higher household incomes over £64,000 (relative to those earning below £32,000) are less likely to avoid peak travel times (significant at 1%, models (B1)

[14] There are too few responses to the other two avoidance strategies, namely Wearing Facemasks and checking air pollution news.

to (B7) in Appendix D, Table D.5).

[Table 4.8] and [Table 4.9]

To summarise the data reveals that standard risk preference measures are not correlated with air pollution avoidance, but air pollution risk perception is. More precisely, the BEG, SOEP-G and SOEP-H showed no significant associations with both aggregated and discrete air pollution outcome measures in this sample. This result does not provide support for the proposition that preventive heath to protect against environmental risks are predicted by risk preferences in the context of air pollution avoidance. Only risk preference measures specific to the context of air pollution risks, was attitudes towards Facemasks which was positively and significantly associated with avoidance. These results provide empirical support for the notion that correlations are stronger between risk measures specific to a given behavioural context (Facemasks) and behaviour within that context (avoidance). It also highlights that even domain-specific risk attitudes, namely SOEP-H, need not predict behaviour across health contexts. Secondly, the results show that associations between risk measures (only Facemasks) and aggregated behavioural outcomes (aggregate avoidance) are stronger. Lastly, it highlights that subject risk beliefs, like air pollution risk perception, are an important explanatory variable, which deserves more policy and research attention.

4.4.5 Cross-context validity

Lastly, the analysis in two steps to consider the question how stable risk measures are across different behavioural contexts. First considering pairwise correlations across the risk measures, and then regression analysis using individual and survey controls.

Table 4.10 reports results of the pairwise correlations together with the significance levels across the different risk measures. First, consider correlations between BEG and other risk measures. If there is stability of risk preferences in the across different contexts, there should be a strong and positive association between SOEP-G (or SOEP-H) and BEG risk, such that those who self-report that they are unwilling to take risks are also the subjects most likely to pick the safer lotteries in the BEG task (e.g. lotteries 1 to 4). Only the SOEP-G shows a small but statistically significant positive correlation of 0.165 ($p = 0.035$). This relationship is more modest than reported in Dohmen et al. (2011) but is in line with Galizzi et al. (2016a), who reported a correlation coefficient of 0.095 ($p = 0.058$) between BEG measure of risk aversion with the SOEP-G. However, they also report a correlation between BEG and SOEP-H of 0.103 ($p = 0.015$), which is not statistically significant in the current study. Note that the BEG measure is not correlated with any other risk measure robustly.

[Table 4.10]

The SOEP-G and SOEP-H measures are positively and significantly correlated at 0.651 (p = 0.000), in line with Dohmen et al. (2011) who found correlation coefficient = 0.476 (p = 0.000) and Galizzi et al. (2016a)who found correlation coefficients of around 0.531 and 0.420 across different samples (p = 0.000 for both samples). As expected, Lights and Helmets are positively and significantly associated with each other (correlation coefficient = 0.380, p = 0.000). The importance of face-masks is positively and significantly associated with lights (correlation coefficient = 0.259, p = 0.014) but not Helmets. None of the standard measures of risk (i.e., BEG, SOEP-G and SOEP-H) is significantly correlated with any of the sub-domain specific precautionary attitudes towards Lights, Helmets or Facemasks. Finally, Facemasks and APRP are positively and significantly correlated (correlation coefficient = 0.461, p = 0.000). Somewhat counter-intuitively, we find a low but positive and significant correlation between SOEP-G and APRP as the correlation coefficient = 0.162 (p = 0.027), and it is unclear why this relationship exists.

The results from the correlations are corroborated from the ordered probit regression models and are qualitatively similar. I briefly summarise the key results in the text, noting that the full specifications are available in Appendix D (Tables D.7 to D.9). For instance, when SOEP-G is regressed on BEG risk with and without survey and individual controls (in Table D.7, models (2)), the coefficient on the BEG risk measure is positive and significant at the 5% level. When SOEP-H is the outcome variable, the coefficient on the BEG risk measure is positive and but not significant, even when survey and individual controls are added. Only APRP positively and significantly predicts Facemasks (at 1% level, Table D.8 model (4)).

When we consider models that include individual control variables, several other results are to be noted. First, we obtain mixed results on the association between reporting gender as female and risk aversion. The current analysis does not replicate the well-established empirical observation that women are more risk-averse than men (e.g. in Eckel and Grossman (2002) and Dohmen et al. (2011)) when gender is regressed on BEG and SOEP-G risk measures. More precisely, the coefficient on female is negative but not statistically significant (in model (1) and (4) from Table D.7, male is the omitted category). However, the coefficient on female is negative and weakly significant when regressed on SOEP-H, suggesting that women are more risk-averse in the health domain.

This is also consistent when we consider the relationship between gender and precautionary attitudes towards Lights, Helmets and Facemasks. When the gender variable regressed on Lights, Helmets and Facemasks, the coefficient on females is positive and significant across specifications (with different measures of risk and individual and survey controls). These results suggest that women are not necessarily more risk averse in this sample and depend on the behavioural context. This result is in line with studies which observe that differences in risk aversion by gender can depend on the decision task at hand and its contextual features (Schubert et al., 1999; Filippin and Crosetto, 2016). Conversely, women perceive higher risk from air pollution relative to men (Table D.9, without and with individual controls and risk measures) and this is in line with the literature on the while male effect (e.g. in Finucane et al. (2000)).

Second, higher age also associated with risk measures; as expected we find falling in the highest age category (i.e., over 55 years) is associated with higher risk aversion by the BEG measure (significant at 5%, model (1) from Table D.7, omitted variable is age category of 18 to 35 years) but not SOEP-G and SOEP-H (negative but not significant at conventional levels). However, there is a weak negative relationship between Helmets and being over 55 years old (significant at 10%) and a stronger negative association with Facemasks (significant at 5%, Table D.9). Third, we also find that income is not a reliable predictor of different risk measures in this sample. Lastly, greater cycling frequency is negatively associated with Helmets and positively associated with Facemasks (all coefficients significant at the 5% level, models (B1) to (B3) and (C1) to (C4) respectively in Table D.8).

To sum up, the data reveals weak support for strong cross-context validity across different risk preferences measures across domains. First, there is a significant and positive association between BEG and SOEP-G but no significant association between BEG and any other risk measure. Second, there is a positive and significant association between SOEP-G and SOEP-H. However, there is also no relationship between standard risk measures and sub-domain precautionary attitudes (towards Lights, Helmets or Facemasks). There is also no linkage between BEG and SOEP-H with APRP. But a positive and significant relationship (that is unexpected) exists between APRP and SOEP-G. Fourth, there is a stable correlation between sub-domain specific attitudes within behavioural contexts: risk-taking while cycling (Lights and Helmet) and air pollution avoidance (Facemasks and APRP), and to a limited extent across behavioural contexts (Lights and Facemasks). These mixed results are consistent with previous studies findings like Galizzi et al. (2016a), who also find low correlations between different risk preferences across types of methods and behavioural domains.

4.4.6 Robustness checks and limitations

To increase the robustness of the estimated results, all the models include survey controls and individual controls for socio-demographic and behavioural differences across subjects. Overall our results suggest that the introduction of additional explanatory variables through survey and individual controls does not alter results on the behavioural validity or cross-context correlations of the risk measures. I also replicate the entire analysis by using a restricted sample of observations collected in the main survey location. The analysis is also replicated using binary outcomes for risk-taking and avoidance with qualitatively similar results. To account for small sample bias, I replicate the analysis using Firth-Logistic regressions where the results show weaker associations but remain more or less similar. All these results are omitted for brevity but available on request.

This study is not without several limitations. The experimental survey follows a validated lab paradigm and has the advantage of yielding greater control and therefore internal validity. Also, targeting the relevant population and setting increases the applicability of the results to a broader population of urban cyclists. I also attempt to mitigate ordering and anchoring effects by randomising the order of questions in the survey (as previously discussed), and cross-check observed values to the previous literature. However, a possible threat to internal validity is the imprecise measurement of the risk measures. This can be due to noise as discussed more extensively in Filippin and Crosetto (2016) and Dave et al. (2010).

Secondly, like previous studies on the topic, the empirical relationship between risk measures and behaviour is not causal. There are numerous other variables which can impact the directed of the observed relationship, such as cognitive ability or mood, omitted from this study. In addition, the study does not measure risk perception of cycling itself, has also been linked to risk-taking transport behaviour in other studies (Ulleberg and Rundmo, 2003; Machin and Sankey, 2008). Other types of economic preference parameters, which are of interest in this setting include ambiguity aversion, prudence and temperance, and time preferences to name a few (Eeckhoudt and Gollier, 2005; Galizzi et al., 2017; Bradford et al., 2017). There is also possible reverse causality between self-reported behaviour and some covariates: for instance, if the number of avoidance actions determines air pollution risk perception (e.g. someone who avoids main roads and peak travel time and therefore believes more actively in the air pollution health risks). Keeping in mind these limitations, I attempt to assess the robustness of these associations, by using individual and survey covariates, and restricting the sample, as previously discussed.

Thirdly, given the different types of behavioural outcome considered, it may be possible that significant results could occur due to chance. However, it is clear from the results that there are mixed results across behaviours and risk measures, and significant results are often in the expected direction according to previous empirical evidence and theory. Moreover, we do not find expected associations on numerous fronts- especially regarding aggregate air pollution avoidance, as well as numerous individual risk-taking and avoidance choices. Like previous studies, this one also relies on self-reports of behaviour, which may suffer from hypothetical bias, recall error and Hawthorne effects. To reduce potential Hawthorne effects, the subject completed the survey alone on the tablet, and the surveyor could not see the responses.

Lastly, the convenience sampling method used in the field attracted only those cyclists with the time and the inclination to participate in the survey, rather than a representative sample from across London. This can reduce the external validity of the results if the population of cyclists excluded from the study have vastly different preferences and behaviour.

4.5 Discussion and conclusion

Risk preferences are widely considered a primitive to understand health behaviours. The choice of risk measure is an essential question to verify if an empirical relationship between risk preference and behaviour exists. There is no agreement about the 'ideal' method given the range experimental and questionnaire methods developed by both economists and psychologists. This debate is interlaced with those about whether and how risk preferences vary across behavioural domains and methodologies. To further this debate, there is a need to accumulate more evidence on the behavioural and cross-context validity of risk preferences.

This study contributes to the literature by exploring how experimental and survey risk measures that capture the willingness to take risks in different domains correlate with behaviour in two novel settings: risk-taking and air pollution avoidance while cycling. It uses a lab-in-the-field experiment to elicit incentive-compatible risk preferences (through the Binswanger-Eckel-Grossman task or BEG), and self-assessments of the willingness to take risks in general and health domains (SOEP-G and SOEP-H respectively). It also measures self-assessments of precautionary attitudes towards items in the cycling safety kit, namely Lights, Helmets and Facemasks (sub-domain attitudes), and Air Pollution Risk Perception (APRP). It is one of the few studies to bring together different risk and behavioural measures, alongside precautionary attitudes and subjective risk beliefs in the field setting.

The main result is that domain-specific risk preferences are closely associated with risk-taking while cycling, but risk preferences are not associated with air pollution avoidance. More specifically, SOEP-H and precautionary attitudes towards items in the cycling safety kit, namely Lights and Helmets are more strongly associated with the aggregate measure of risk-taking while cycling. However, none of the standard risk measures predicts either the extent of avoidance undertaken or individual avoidance behaviours. The only variables which do so, are APRP and Facemasks. More generally, there are stronger correlations between aggregated behavioural outcomes and risk measures, rather than individual behaviours, suggesting studies should collect more detailed data to study underlying associations. Also, although different risk measures correlate with each other, their associations are imperfect (e.g. BEG correlated with SOEP-G but not SOEP-H or Lights, Helmets and Facemasks). Taken together, these results lend support for the idea that risk preference measures need not strongly associate across multiple behavioural domains and both the risk preference and behavioural outcome measure determines observed empirical patterns.

One implication of these results is that future researchers need to use risk measures that are lie close to the behavioural domain under study. By measuring a more comprehensive set of both risk preference and behavioural outcome measures, they could detect more robust underlying behavioural tendencies. But given the weak cross-context validity, it is not clear that risk preferences that are elicited using context-specific tasks are particularly good at capturing risk preferences in other behavioural contexts. Another implication, is that risk perception rather than risk aversion is correlated with air pollution avoidance, and future studies can systematically assess whether this result holds in other samples and behavioural contexts. This is also interesting from a policy standpoint, as it suggests that changing risk perception may have behavioural implications. However, this line of policy should be pursued with cautio, as risk perception is associated with affect-based decision making form worry or anxiety about air pollution. There may be limited scope of behavioural change due to emotional numbing, apart from the well-being implications of a population excessively worried about air pollution risks (Weber, 2010).

Methodologically, the study employs a standardized paradigm in the field context, to maintain tight control and enhance internal validity, while allowing for direct comparisons across contexts and populations. However, this study is not without some limitations as discussed in the previous section. A replication across new contexts and populations could reveal whether these results are externally valid. Along these lines, future research could also consider a wider range of behaviours from a more representative sample to re-evaluate the associations between risk measures and behavioural outcomes. The current study also raises some other questions for future research. For instance, would the results persist with different risk elicitation methods or different incentives? Apart from the behavioural validity and cross-context validity, are risk preferences of an individual stable across time across different contexts? Can avoidance be better explained by jointly elicited time and risk preferences, or other higher-order preferences like prudence? More generally, does the mixed evidence between risk measures and behavioural outcomes persist across a broader set of behaviours? In the last case, it is important to note that both the risk measure and behavioural outcome in a context matters for the empirical relationship.

Bibliography

Aldred, R., Woodcock, J., and Goodman, A. (2016). Does more cycling mean more diversity in cycling? *Transport reviews*, 36(1):28–44.

Anderson, L. R. and Mellor, J. M. (2008). Predicting health behaviors with an experimental measure of risk preference. *Journal of health economics*, 27(5):1260–1274.

Arrow, K. J. (1965). *Aspects of the theory of risk-bearing*. Yrjö Jahnssonin Säätiö.

Arrow, K. J. (1968). The economics of moral hazard: further comment. *The American Economic Review*, 58(3):537–539.

Attanasi, G., Georgantzís, N., Rotondi, V., and Vigani, D. (2016). Lottery-and survey-based risk attitudes linked through a multichoice elicitation task. *Theory and Decision*, pages 1–32.

Barham, B. L., Chavas, J.-P., Fitz, D., Salas, V. R., and Schechter, L. (2014). The roles of risk and ambiguity in technology adoption. *Journal of Economic Behavior & Organization*, 97:204–218.

Barseghyan, L., Molinari, F., O'Donoghue, T., and Teitelbaum, J. C. (2018). Estimating risk preferences in the field. *Journal of Economic Literature*, Forthcoming.

Barseghyan, L., Prince, J., and Teitelbaum, J. C. (2011). Are risk preferences stable across contexts? evidence from insurance data. *American Economic Review*, 101(2):591–631.

Barsky, R. B., Juster, F. T., Kimball, M. S., and Shapiro, M. D. (1997). Preference parameters and behavioral heterogeneity: An experimental approach in the health and retirement study. *The Quarterly Journal of Economics*, 112(2):537–579.

Becker, A., Deckers, T., Dohmen, T., Falk, A., and Kosse, F. (2012). The relationship between economic preferences and psychological personality measures. *Annual Review of Economics*, 4(1):453–478.

Berg, J., Dickhaut, J., and McCabe, K. (2005). Risk preference instability across institutions: A dilemma. *Proceedings of the National Academy of Sciences of the United States of America*, 102(11):4209–4214.

Binswanger, H. P. (1980). Attitudes toward ris: Experimental measurement in rural india. *American journal of agricultural economics*, 62(3):395–407.

Binswanger, H. P. (1981). Attitudes toward risk: Theoretical implications of an experiment in rural india. *The Economic Journal*, 91(364):867–890.

Blais, A.-R. and Weber, E. (2006). A domain-specific risk-taking (dospert) scale for adult populations. *Judgment and Decision Making*, 1(1).

Blondel, S., Lohéac, Y., and Rinaudo, S. (2007). Rationality and drug use: An experimental approach. *Journal of health economics*, 26(3):643–658.

Borghans, L., Duckworth, A. L., Heckman, J. J., and Ter Weel, B. (2008). The economics and psychology of personality traits. *Journal of human Resources*, 43(4):972–1059.

Bradford, D., Courtemanche, C., Heutel, G., McAlvanah, P., and Ruhm, C. (2017). Time preferences and consumer behavior. *Journal of Risk and Uncertainty*, 55(2–3):119–145.

Brick, K. and Visser, M. (2015). Risk preferences, technology adoption and insurance uptake: A framed experiment. *Journal of Economic Behavior & Organization*, 118:383–396.

Briys, E., Schlesinger, H., and vd SCHULENBURG, J.-M. G. (1991). Reliability of risk management: market insurance, self-insurance and self-protection reconsidered. *The Geneva Papers on Risk and Insurance Theory*, 16(1):45–58.

Carman, K. G. and Kooreman, P. (2014). Probability perceptions and preventive health care. *Journal of Risk and Uncertainty*, 49(1):43–71.

Charness, G. and Gneezy, U. (2012). Strong evidence for gender differences in risk taking. *Journal of Economic Behavior & Organization*, 83(1):50–58.

Charness, G., Gneezy, U., and Halladay, B. (2016). Experimental methods: Pay one or pay all. *Journal of Economic Behavior & Organization*, 131:141–150.

Charness, G., Gneezy, U., and Imas, A. (2013). Experimental methods: Eliciting risk preferences. *Journal of Economic Behavior & Organization*, 87:43–51.

Chataway, E. S., Kaplan, S., Nielsen, T. A. S., and Prato, C. G. (2014). Safety perceptions and reported behavior related to cycling in mixed traffic: A comparison between brisbane and copenhagen. *Transportation research part F: traffic psychology and behaviour*, 23:32–43.

Chuang, Y. and Schechter, L. (2015). Stability of experimental and survey measures of risk, time, and social preferences: A review and some new results. *Journal of Development Economics*, 117:151–170.

Collard, L. and Oboeuf, A. (2013). Do dangerous sports specialists play more dangerously? an experimental study on sample selection. *Journal of Risk Research*, 16(1):39–50.

Coppola, M. (2014). Eliciting risk-preferences in socio-economic surveys: How do different measures perform? *The Journal of Socio-Economics*, 48:1–10.

Cox, J. C. and Harrison, G. W. (2008). Risk aversion in experiments: An introduction. In *Risk aversion in experiments*, pages 1–7. Emerald Group Publishing Limited.

Crosetto, P. and Filippin, A. (2013). The "bomb" risk elicitation task. *Journal of Risk and Uncertainty*, 47(1):31–65.

Crosetto, P. and Filippin, A. (2016). A theoretical and experimental appraisal of four risk elicitation methods. *Experimental Economics*, 19(3):613–641.

Croson, R. and Gneezy, U. (2009). Gender differences in preferences. *Journal of Economic literature*, 47(2):448–74.

Csermely, T. and Rabas, A. (2016). How to reveal people's preferences: Comparing time consistency and predictive power of multiple price list risk elicitation methods. *Journal of risk and uncertainty*, 53(2-3):107–136.

Dave, C., Eckel, C. C., Johnson, C. A., and Rojas, C. (2010). Eliciting risk preferences: When is simple better? *Journal of Risk and Uncertainty*, 41(3):219–243.

Deck, C., Lee, J., and Reyes, J. (2008). Risk attitudes in large stake gambles: evidence from a game show. *Applied Economics*, 40(1):41–52.

Deck, C., Lee, J., Reyes, J. A., and Rosen, C. C. (2013). A failed attempt to explain within subject variation in risk taking behavior using domain specific risk attitudes. *Journal of Economic Behavior & Organization*, 87:1–24.

DFT (2015). Reported road casualties in great britain: main results 2015. Technical report, Dpartment for Trasport.

Dionne, G. and Eeckhoudt, L. (1985). Self-insurance, self-protection and increased risk aversion. *Economics Letters*, 17(1-2):39–42.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., and Wagner, G. G. (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association*, 9(3):522–550.

Dolan, P. and Galizzi, M. M. (2015). Like ripples on a pond: Behavioral spillovers and their implications for research and policy. *Journal of Economic Psychology*, 47:1–16.

Dulleck, U., Fooken, J., and Fell, J. (2015). Within-subject intra-and inter-method consistency of two experimental risk attitude elicitation methods. *German Economic Review*, 16(1):104–121.

Eckel, C. C. and Grossman, P. J. (2002). Sex differences and statistical stereotyping in attitudes toward financial risk. *Evolution and human behavior*, 23(4):281–295.

Eckel, C. C. and Grossman, P. J. (2008). Forecasting risk attitudes: An experimental study using actual and forecast gamble choices. *Journal of Economic Behavior & Organization*, 68(1):1–17.

Eeckhoudt, L. and Gollier, C. (2005). The impact of prudence on optimal prevention. *Economic Theory*, 26(4):989–994.

Ehrlich, I. and Becker, G. S. (1972). Market insurance, self-insurance, and self-protection. *Journal of political Economy*, 80(4):623–648.

Einav, L., Finkelstein, A., Pascu, I., and Cullen, M. R. (2012). How general are risk preferences? choices under uncertainty in different domains. *American Economic Review*, 102(6):2606–38.

Falk, A., Becker, A., Dohmen, T. J., Enke, B., and Huffman, D. (2015). The nature and predictive power of preferences: Global evidence. Technical Report IZA Discussion Paper Number 9504, Maastricht University.

Filippin, A. and Crosetto, P. (2016). A reconsideration of gender differences in risk attitudes. *Management Science*, 62(11):3138–3160.

Finucane, M. L., Slovic, P., Mertz, C. K., Flynn, J., and Satterfield, T. A. (2000). Gender, race, and perceived risk: The'white male'effect. *Health, risk & society*, 2(2):159–172.

Fischbacher, U., Schudy, S., and Teyssier, S. (2015). Heterogeneous preferences and investments in energy saving measures. Technical report, Munich Discussion Paper.

Fishman, E. (2016). Bikeshare: A review of recent literature. *Transport Reviews*, 36(1):92–113.

Frey, R., Pedroni, A., Mata, R., Rieskamp, J., Hertwig, R., and Hertwig (2017). Risk preference shares the psychometric structure of major psychological traits. *Science advances*, 3(10):e1701381.

Galizzi, M. M., Harrison, G. W., and Miraldo, M. (2017). Experimental methods and behavioral insights in health economics: Estimating risk and time preferences in health. *Working Ppaper*.

Galizzi, M. M., Machado, S. R., and Miniaci, R. (2016a). Temporal stability, cross-validity, and external validity of risk preferences measures: Experimental evidence from a uk representative sample. *Working paper*.

Galizzi, M. M., Miraldo, M., and Stavropoulou, C. (2016b). In sickness but not in wealth: Field evidence on patients' risk preferences in financial and health domains. *Medical Decision Making*, 36(4):503–517.

Ganzach, Y., Ellis, S., Pazy, A., and Ricci-Siag, T. (2008). On the perception and operationalization of risk perception. *Judgment and Decision Making*, 3(4):317.

Gneezy, U. and Imas, A. (2017). Lab in the field: Measuring preferences in the wild. In *Handbook of economic field experiments*, volume 1, pages 439–464. Elsevier.

Gneezy, U. and Potters, J. (1997). An experiment on risk taking and evaluation periods. *The Quarterly Journal of Economics*, 112(2):631–645.

Goldzahl, L. (2017). Contributions of risk preference, time orientation and perceptions to breast cancer screening regularity. *Social Science & Medicine*, 185:147–157.

Gollier, C., Hammitt, J. K., and Treich, N. (2013). Risk and choice: A research saga. *Journal of risk and uncertainty*, 47(2):129–145.

Halek, M. and Eisenhauer, J. G. (2001). Demography of risk aversion. *Journal of Risk and Insurance*, pages 1–24.

Handy, S., Van Wee, B., and Kroesen, M. (2014). Promoting cycling for transport: research needs and challenges. *Transport reviews*, 34(1):4–24.

Hanoch, Y., Johnson, J. G., and Wilke, A. (2006). Domain specificity in experimental measures and participant recruitment: An application to risk-taking behavior. *Psychological Science*, 17(4):300–304.

Harrison, G. W., Hofmeyr, A., Ross, D., and Swarthout, J. T. (2017). Risk preferences, time preferences and smoking behaviour.

Harrison, G. W., Lau, M. I., and Rutström, E. E. (2007). Estimating risk attitudes in denmark: A field experiment. *The Scandinavian Journal of Economics*, 109(2):341–368.

Harrison, G. W., Lau, M. I., and Rutström, E. E. (2010). Individual discount rates and smoking: Evidence from a field experiment in denmark. *Journal of health economics*, 29(5):708–717.

Harrison, G. W. and List, J. A. (2004). Field experiments. *Journal of Economic literature*, 42(4):1009–1055.

Harrison, G. W. and Rutström, E. (2008). Risk aversion in the laboratory. In *Risk aversion in experiments*, pages 41–196. Emerald Group Publishing Limited.

Hey, J. D., Morone, A., and Schmidt, U. (2009). Noise and bias in eliciting preferences. *Journal of Risk and Uncertainty*, 39(3):213–235.

Holt, C. A. and Laury, S. K. (2002). Risk aversion and incentive effects. *American economic review*, 92(5):1644–1655.

Ioannou, C. A. and Sadeh, J. (2016). Time preferences and risk aversion: Tests on domain differences. *Journal of Risk and Uncertainty*, 53(1):29–54.

Isaac, R. M. and James, D. (2000). Just who are you calling risk averse? *Journal of Risk and Uncertainty*, 20(2):177–187.

Josef, A. K., Richter, D., Samanez-Larkin, G. R., Wagner, G. G., Hertwig, R., and Mata, R. (2016). Stability and change in risk-taking propensity across the adult life span. *Journal of personality and social psychology*, 111(3):430.

Kahan, D. M., Peters, E., Wittlin, M., Slovic, P., Ouellette, L. L., Braman, D., and Mandel, G. (2012). The polarizing impact of science literacy and numeracy on perceived climate change risks. *Nature climate change*, 2(10):732.

Kahneman, D. and Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2):263–292.

Katapodi, M. C., Lee, K. A., Facione, N. C., and Dodd, M. J. (2004). Predictors of perceived breast cancer risk and the relation between perceived risk and breast cancer screening: a meta-analytic review. *Preventive medicine*, 38(4):388–402.

Khwaja, A., Sloan, F., and Salm, M. (2006). Evidence on preferences and subjective beliefs of risk takers: The case of smokers. *International Journal of Industrial Organization*, 24(4):667–682.

Lawson, A. R., Pakrashi, V., Ghosh, B., and Szeto, W. (2013). Perception of safety of cyclists in dublin city. *Accident Analysis & Prevention*, 50:499–511.

Leiserowitz, A. (2006). Climate change risk perception and policy preferences: The role of affect, imagery, and values. *Climatic change*, 77(1-2):45–72.

Lejuez, C. W., Read, J. P., Kahler, C. W., Richards, J. B., Ramsey, S. E., Stuart, G. L., Strong, D. R., and Brown, R. A. (2002). Evaluation of a behavioral measure of risk taking: the balloon analogue risk task (bart). *Journal of Experimental Psychology: Applied*, 8(2):75.

Liu, E. M. (2013). Time to change what to sow: Risk preferences and technology adoption decisions of cotton farmers in china. *Review of Economics and Statistics*, 95(4):1386–1403.

Liu, E. M. and Huang, J. (2013). Risk preferences and pesticide use by cotton farmers in china. *Journal of Development Economics*, 103:202–215.

Lönnqvist, J.-E., Verkasalo, M., Walkowitz, G., and Wichardt, P. C. (2015). Measuring individual risk attitudes in the lab: Task or ask? an empirical comparison. *Journal of Economic Behavior & Organization*, 119:254–266.

Loomes, G. and Pogrebna, G. (2014). Measuring individual risk attitudes when preferences are imprecise. *The Economic Journal*, 124(576):569–593.

Lusk, J. L. and Coble, K. H. (2005). Risk perceptions, risk preference, and acceptance of risky food. *American Journal of Agricultural Economics*, 87(2):393–405.

Machin, M. A. and Sankey, K. S. (2008). Relationships between young drivers' personality characteristics, risk perceptions, and driving behaviour. *Accident analysis & prevention*, 40(2):541–547.

Mather, M., Mazar, N., Gorlick, M. A., Lighthall, N. R., Burgeno, J., Schoeke, A., and Ariely, D. (2012). Risk preferences and aging: The "certainty effect" in older adults' decision making. *Psychology and aging*, 27(4):801.

Mishra, S. (2014). Decision-making under risk: Integrating perspectives from biology, economics, and psychology. *Personality and Social Psychology Review*, 18(3):280–307.

Mousavi, S. and Gigerenzer, G. (2014). Risk, uncertainty, and heuristics. *Journal of Business Research*, 67(8):1671–1678.

Nash, N., Whitmarsh, L., Capstick, S., Hargreaves, T., Poortinga, W., Thomas, G., Sautkina, E., and Xenias, D. (2017). Climate-relevant behavioral spillover and the potential contribution of social practice theory. *Wiley Interdisciplinary Reviews: Climate Change*, 8(6).

Nelson, J. A. (2015). Are women really more risk-averse than men? a re-analysis of the literature using expanded methods. *Journal of Economic Surveys*, 29(3):566–585.

NIHR (2017). Tips to reduce your exposure whilst cycling. http://www.breathelondon.org/south-east/cycling [Acessed on: June 2017].

Paulsen, D., Platt, M., Huettel, S. A., and Brannon, E. M. (2011). Decision-making under risk in children, adolescents, and young adults. *Frontiers in psychology*, 2:72.

Petrolia, D. R., Landry, C. E., and Coble, K. H. (2013). Risk preferences, risk perceptions, and flood insurance. *Land Economics*, 89(2):227–245.

Picone, G., Sloan, F., and Taylor, D. (2004). Effects of risk and time preference and expected longevity on demand for medical tests. *Journal of Risk and Uncertainty*, 28(1):39–53.

Post, T., Van den Assem, M. J., Baltussen, G., and Thaler, R. H. (2008). Deal or no deal? decision making under risk in a large-payoff game show. *American Economic Review*, 98(1):38–71.

Pratt, J. W. (1964). Risk aversion in the small and in the large. *Econometrica*, 32(1/2):122–136.

Pucher, J., Buehler, R., and Seinen, M. (2011). Bicycling renaissance in north america? an update and re-appraisal of cycling trends and policies. *Transportation research part A: policy and practice*, 45(6):451–475.

Qiu, Y., Colson, G., and Grebitus, C. (2014). Risk preferences and purchase of energy-efficient technologies in the residential sector. *Ecological Economics*, 107:216–229.

Reynaud, A. and Couture, S. (2012). Stability of risk preference measures: results from a field experiment on french farmers. *Theory and decision*, 73(2):203–221.

Reynolds, B., Ortengren, A., Richards, J. B., and de Wit, H. (2006). Dimensions of impulsive behavior: Personality and behavioral measures. *Personality and individual differences*, 40(2):305–315.

Riddel, M. (2012). Comparing risk preferences over financial and environmental lotteries. *Journal of Risk and Uncertainty*, 45(2):135–157.

Riddel, M. and Kolstoe, S. (2013). Heterogeneity in life-duration preferences: Are risky recreationists really more risk loving? *Journal of risk and uncertainty*, 46(2):191–213.

Rustichini, A., DeYoung, C. G., Anderson, J. E., and Burks, S. V. (2016). Toward the integration of personality theory and decision theory in explaining economic behavior: An experimental investigation. *Journal of Behavioral and Experimental Economics*, 64:122–137.

Schubert, R., Brown, M., Gysler, M., and Brachinger, H. W. (1999). Financial decision-making: are women really more risk-averse? *American Economic Review*, 89(2):381–385.

Spence, A., Poortinga, W., Butler, C., and Pidgeon, N. F. (2011). Perceptions of climate change and willingness to save energy related to flood experience. *Nature climate change*, 1(1):46.

Spence, A., Poortinga, W., and Pidgeon, N. (2012). The psychological distance of climate change. *Risk analysis*, 32(6):957–972.

Starmer, C. (2000). Developments in non-expected utility theory: The hunt for a descriptive theory of choice under risk. *Journal of economic literature*, 38(2):332–382.

Steinbach, R., Green, J., Datta, J., and Edwards, P. (2011). Cycling and the city: a case study of how gendered, ethnic and class identities can shape healthy transport choices. *Social science & medicine*, 72(7):1123–1130.

Sutter, M., Kocher, M. G., Glätzle-Rüetzler, D., and Trautmann, S. T. (2013). Impatience and uncertainty: Experimental decisions predict adolescents' field behavior. *American Economic Review*, 103(1):510–31.

Szrek, H., Chao, L.-W., Ramlagan, S., and Peltzer, K. (2012). Predicting (un) healthy behavior: A comparison of risk-taking propensity measures. *Judgment and decision making*, 7(6):716.

TfL (2016). Attitudes towards cycling. Technical report, Transport for London.

Truelove, H. B., Carrico, A. R., Weber, E. U., Raimi, K. T., and Vandenbergh, M. P. (2014). Positive and negative spillover of pro-environmental behavior: An integrative review and theoretical framework. *Global Environmental Change*, 29:127–138.

Tversky, A. and Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and uncertainty*, 5(4):297–323.

Ulleberg, P. and Rundmo, T. (2003). Personality, attitudes and risk perception as predictors of risky driving behaviour among young drivers. *Safety science*, 41(5):427–443.

Verschoor, A., D'Exelle, B., and Perez-Viana, B. (2016). Lab and life: Does risky choice behaviour observed in experiments reflect that in the real world? *Journal of Economic Behavior & Organization*, 128:134–148.

Vieider, F. M., Lefebvre, M., Bouchouicha, R., Chmura, T., Hakimov, R., Krawczyk, M., and Martinsson, P. (2015). Common components of risk and uncertainty attitudes across contexts and domains: Evidence from 30 countries. *Journal of the European Economic Association*, 13(3):421–452.

Volland, B. (2017). The role of risk and trust attitudes in explaining residential energy demand: Evidence from the united kingdom. *Ecological Economics*, 132:14–30.

Weber, E. U. (2010). What shapes perceptions of climate change? *Wiley Interdisciplinary Reviews: Climate Change*, 1(3):332–342.

Weber, E. U., Blais, A.-R., and Betz, N. E. (2002). A domain-specific risk-attitude scale: Measuring risk perceptions and risk behaviors. *Journal of behavioral decision making*, 15(4):263–290.

Woodcock, J., Tainio, M., Cheshire, J., O'Brien, O., and Goodman, A. (2014). Health effects of the london bicycle sharing system: health impact modelling study. *Bmj*, 348:g425.

4.6 Tables and Figures

Table 4.1: Binswager-Eckel-Grossman (BEG) task: lottery choices, expected payoffs, and risk

Gamble	Event A	Event B	Probability	Expected payofs	Risk	CRRA range
1	£4.00	£4.00	50/50	£4.00	0.00	r >2.00
2	£6.00	£3.00	50/50	£4.50	2.12	0.669 <r <2.00
3	£8.00	£2.00	50/50	£5.00	4.24	0.382 <r <0.669
4	£10.00	£1.00	50/50	£5.50	6.36	0.197 <r <0.382
5	£12.00	£0.00	50/50	£6.00	8.49	r <0.197

Notes: Risk is measured as standard deviation of expected payoff. The value of the ranges of r are estimated from the function $U = \frac{x^{(1-r)}}{(1-r)}$, assuming constant relative risk aversion utility (CRRA).

Table 4.2: Sample characteristics

Variable	Variable category	% Share	Mean	SD	Min	Max
Cyclist type	Rec	24.86	2.436	0.864	1	3
	Com	6.63				
	Rec + Com	68.51				
Cyling frequency	<1pm	2.21	4.094	1.037	1	5
	1-2pm	8.84				
	1 pw	9.39				
	2-4 pw	36.46				
	>= 5pw	43.09				
AP knowledge	1	12.71	2.928	1.243	1	5
	2	29.83				
	3	22.1				
	4	22.65				
	5	12.71				
Age	18-34	37.02	1.768	0.700	1	4
	35-54	50.83				
	>55	10.50				
	PNTS	1.66				
Gender	Male	66.30	1.359	0.546	1	3
	Female	32.60				
	PNTS	1.10				
Ethnic group	White	76.80	1.304	0.598	1	3
	BAME	16.02				
	Other/PNTS	7.18				
Income	<£32,000	17.68	2.663	0.938	1	4
	£32,000 to $\leq$ £64,000	13.26				
	>£64,000	54.14				
	DK/PNTS	14.92				
Education	<UG	20.99	2.138	0.787	1	4
	UG	48.07				
	>UG	27.07				
	PNTS	3.87				
Sample (N, number of observations)						181

Notes: Rec: Recreational; Com: commuter; pm: per month; pw: per week; AP knowledge: Air pollution knowledge score (values can range from 0 (minimum) to 5 (maximum)); BAME: Black Asian Minority Ethnic; UG: Undergraduate degree; DK: Don't know; PNTS: Prefer not to say.

Table 4.3: Descriptive statistics: Risk measures and (aggregate) dependent variables

Variable, brief description	Mean	SD	Max	Min
BEG, incentive-compatible risk preferences	2.619	1.575	1	5
SOEP-G, self-assessment general risk attitude	7.050	2.242	1	11
SOEP-H, self-assessment health risk attitude	6.287	2.520	1	11
APRP, self-assessment air pollution risk perception	7.956	2.035	1	11
Lights, self-assessment importance of item in a cycling safety kit	3.967	1.048	1	5
Helmet, self-assessment importance of item in a cycling safety kit	4.249	1.110	1	5
Facemask, self-assessment importance of item in a cycling safety kit	1.983	1.098	1	5
# Avoidance, self-report of air pollution avoidance behaviour (aggregate)	1.735	1.323	0	6
Risk-taking, self-report of risk-taking while cycling (aggregate)	9.569	2.833	6	20

Notes: BEG: Binswanger-Eckel-Grossman risk measure; SOEP-G(H): German Socio-Economic Panel General (Health) risk attitude; APRP: Air Pollution Risk Perception; # Avoidance : Event (aggregate) count of different avoidance behaviours; Risk-taking: Aggregate score of different risk-taking behaviours while cycling.

Table 4.4: Risk measures and risk-taking while cycling (aggregate)

Dependent variable:	Risk-taking while cycling									
Ordered logistic models:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
BEG	0.104	0.147								
	(0.091)	(0.104)								
SOEP-G			0.125*	0.121*						
			(0.067)	(0.072)						
SOEP-H					0.197***	0.214***				
					(0.069)	(0.068)				
Lights							-0.492***	-0.485***		
							(0.127)	(0.147)		
Helmet									-0.625***	-0.791***
									(0.113)	(0.134)
Observations	181	181	181	181	181	181	181	181	181	181
Survey controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Dependent variable is the aggregate score of all risk-taking behaviours while cycling from 6 ('Never' for any behaviour) to 20 ('Always' for all behaviours). Risk measures include BEG: Binswanger-Eckel-Grossman risk measure; SOEP-G(H): German Socio-Economic Panel General (Health) risk attitude; Lights and Helmet: rating of importance of item in a cycling safety kit. The coefficients are the ordered log-odds (logit) regression coefficients, where the response variable level is expected to change by its respective regression coefficient in the ordered log-odds scale for a one unit increase in the predictor, while the other variables in the model are held constant. Individual controls include cyclist type, cycling frequency, air pollution knowledge, age, gender, ethnicity, income and education covariates. Survey controls include surveyor, location and time of day factor covariates. All models use robust standard errors. Significance levels reported at *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4.5: Risk measures and risk-taking behaviours I: Red lights, Music and No lights

Dependent variables:	(A) Red lights					(B) Music					(C) No light				
Ordered logistic models:	(A1)	(A2)	(A3)	(A4)	(A5)	(B1)	(B2)	(B3)	(B4)	(B5)	(C1)	(C2)	(C3)	(C4)	(C5)
BEG	-0.011					0.114					-0.113				
	(0.110)					(0.116)					(0.122)				
SOEP-G		0.080					0.192*					0.145*			
		(0.092)					(0.107)					(0.088)			
SOEP-H			0.154*					0.201**					0.092		
			(0.079)					(0.083)					(0.081)		
Lights				-0.369**					-0.106					-0.504***	
				(0.174)					(0.172)					(0.192)	
Helmet					-0.387**					-0.076					-0.096
					(0.188)					(0.188)					(0.181)
Observations	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181
Survey controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable is the score of different risk-taking behaviours while cycling from 1 (Never) to 5 (Always). TIndependent variables include BEG: Binswanger-Eckel-Grossman risk measure; SOEP-G(H): German Socio-Economic Panel General (Health) risk attitude; Lights and Helmet: rating of importance of item in a cycling safety kit. The coefficients are the ordered log-odds (logit) regression coefficients, where the response variable level is expected to change by its respective regression coefficient in the ordered log-odds scale for a one unit increase in the predictor, while the other variables in the model are held constant. Individual controls include cyclist type, cycling frequency, air pollution knowledge, age, gender, ethnicity, income and education covariates. Survey controls include surveyor, location and time of day factor covariates. All models use robust standard errors. Significance levels reported at *** p<0.01, ** p<0.05, * p<0.1.

Table 4.6: Risk measures and risk-taking behaviours II: Mobile, No helmet and Alcohol

Dependent variables:	(D) Mobile					(E) No helmet					(F) Alcohol				
Ordered logistic models:	(D1)	(D2)	(D3)	(D4)	(D5)	(E1)	(E2)	(E3)	(E4)	(E5)	(F1)	(F2)	(F3)	(F4)	(F5)
BEG	0.264**					0.012					0.167				
	(0.126)					(0.117)					(0.108)				
SOEP-G		0.172					-0.045					0.082			
		(0.123)					(0.078)					(0.074)			
SOEP-H			0.237***					0.124*					0.107		
			(0.086)					(0.074)					(0.073)		
Lights				-0.229					-0.355*					-0.240	
				(0.194)					(0.186)					(0.172)	
Helmet					-0.433**					-1.250***					-0.362**
					(0.219)					(0.238)					(0.172)
Observations	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181
Survey controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable is the score of different risk-taking behaviours while cycling from 1 (Never) to 5 (Always). Independent variables include BEG: Binswanger-Eckel-Grossman risk measure; SOEP-G(H) German Socio-Economic Panel General (Health) risk attitude; Lights and Helmet: rating of importance of item in a cycling safety kit. The coefficients are the ordered log-odds (logit) regression coefficients where the response variable level is expected to change by its respective regression coefficient in the ordered log-odds scale for a one unit increase in the predictor, while the other variables in the model are held constant. Individual controls include cyclist type, cycling frequency, air pollution knowledge, age, gender, ethnicity, income and education covariates. Survey controls include surveyor, location and time of day factor covariates. All models use robust standard errors. Significance levels reported at *** p<0.01, ** p<0.05, * p<0.1.

Table 4.7: Risk measures and air pollution avoidance (aggregate)

Dependent variable:	# Air pollution avoidance													
Poisson regression models	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
BEG	-0.005	-0.000												
	(0.036)	(0.036)												
SOEP-G			-0.011	-0.020										
			(0.027)	(0.027)										
SOEP-H					0.006	0.008								
					(0.024)	(0.021)								
Lights							0.068	0.091*						
							(0.051)	(0.055)						
Helmet									-0.012	0.020				
									(0.048)	(0.050)				
Facemask											0.188***	0.191***		
											(0.051)	(0.054)		
APRP													0.086***	0.088***
													(0.030)	(0.030)
AP knowledge		0.139***		0.143***		0.139***		0.150***		0.141***		0.127***		0.137***
		(0.043)		(0.044)		(0.043)		(0.043)		(0.043)		(0.040)		(0.042)
Constant	0.288	0.342	0.341	0.479	0.243	0.303	-0.009	0.017	0.324	0.243	-0.120	0.005	-0.447	-0.310
	(0.294)	(0.400)	(0.319)	(0.426)	(0.298)	(0.392)	(0.358)	(0.442)	(0.358)	(0.468)	(0.304)	(0.394)	(0.370)	(0.450)
Observations	181	181	181	181	181	181	181	181	181	181	181	181	181	181
Survey controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Dependent variable: Air pollution avoidance is an event count from 0 (no avoidance) to 6 (6 types of avoidance behaviours). Independent variables (risk measures): BEG: Binswanger-Eckel-Grossman risk measure; SOEP-G(H): German Socio-Economic Panel General (Health) risk attitude; APR: Air Pollution Risk Perception. The coefficients give increase in the predicted log odds units for a one-unit increase in predictor variable. Individual covariates include cycling behaviour (cyclist type, cycling frequency), socio-demographic attributes (age, gender, education, income, ethnicity), and surveyor covariates include categorical variables for surveyor, location and time of day. All regressions use robust standard errors. Significance levels reported at *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4.8: Risk measures and air pollution avoidance behaviours I: Avoiding Main roads and Peak travel

Dependent variables:	(A) Avoiding main roads							(B) Avoiding peak travel						
Logistic models:	(A1)	(A2)	(A3)	(A4)	(A5)	(A6)	(A7)	(B1)	(B2)	(B3)	(B4)	(B5)	(B6)	(B7)
BEG	-0.157							-0.215						
	(0.104)							(0.133)						
SOEP-G		-0.141*							-0.017					
		(0.077)							(0.093)					
SOEP-H			-0.065							0.125				
			(0.069)							(0.082)				
Lights				0.357**							-0.060			
				(0.175)							(0.207)			
Helmet					0.251							0.017		
					(0.166)							(0.183)		
Facemask						0.393**							0.738***	
						(0.175)							(0.241)	
APRP							0.093							0.138
							(0.083)							(0.107)
AP knowledge	0.135	0.147	0.121	0.172	0.157	0.095	0.117	0.449**	0.413**	0.419***	0.405**	0.411**	0.383**	0.417**
	(0.137)	(0.138)	(0.136)	(0.137)	(0.136)	(0.137)	(0.135)	(0.179)	(0.173)	(0.159)	(0.170)	(0.170)	(0.157)	(0.166)
Constant	-1.256	-0.831	-1.429	-3.050**	-2.940**	-2.449**	-2.443*	-0.221	-0.735	-1.553	-0.654	-0.938	-2.231	-1.786
	(1.235)	(1.301)	(1.223)	(1.383)	(1.428)	(1.231)	(1.327)	(1.801)	(1.853)	(1.680)	(1.949)	(1.883)	(1.976)	(1.787)
Observations	181	181	181	181	181	181	181	181	181	181	181	181	181	181
Survey controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable: Avoidance behaviours take on values of 0 (no) to 1 (yes). Independent variables (risk measures): BEG: Binswanger-Eckel-Grossman risk measure; SOEP-G(H): German Socio-Economic Panel General (Health) risk attitude; APR: Air Pollution Risk Perception. The coefficients give increase in the predicted log odds units for a one-unit increase in predictor variable. Individual covariates include cycling behaviour (cyclist type, cycling frequency), socio-demographic attributes (age, gender, education, income, ethnicity), and surveyor covariates include categorical variables for surveyor, location and time of day. All regressions use robust standard errors. Significance levels reported at *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4.9: Risk measures and air pollution avoidance behaviours II: Avoiding stopping behind vehicles and biking short distances

Dependent variables:	(C) Avoiding stopping behind vehicles							(D) Biking short distances						
Logistic models:	(C1)	(C2)	(C3)	(C4)	(C5)	(C6)	(C7)	(D1)	(D2)	(D3)	(D4)	(D5)	(D6)	(D7)
BEG	0.081							0.066						
	(0.109)							(0.113)						
SOEP-G		0.001							-0.024					
		(0.075)							(0.085)					
SOEP-H			-0.010							0.027				
			(0.065)							(0.074)				
Lights				0.019							0.201			
				(0.167)							(0.160)			
Helmet					0.099							-0.072		
					(0.161)							(0.167)		
Facemask						0.433**							-0.237	
						(0.189)							(0.188)	
APRP							0.171*							0.086
							(0.092)							(0.092)
AP knowledge	0.164	0.169	0.169	0.171	0.183	0.146	0.167	0.350**	0.358**	0.354**	0.378***	0.345**	0.376**	0.352**
	(0.138)	(0.137)	(0.137)	(0.138)	(0.139)	(0.140)	(0.141)	(0.139)	(0.142)	(0.140)	(0.143)	(0.141)	(0.146)	(0.140)
Constant	0.103	0.314	0.368	0.254	-0.157	-0.443	-0.986	-1.526	-1.200	-1.475	-2.044	-0.999	-0.948	-1.979
	(1.124)	(1.185)	(1.126)	(1.208)	(1.345)	(1.157)	(1.290)	(1.191)	(1.228)	(1.185)	(1.264)	(1.361)	(1.190)	(1.368)
Observations	177	177	177	177	177	177	177	172	172	172	172	172	172	172
Survey controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable: Air pollution avoidance is an event count from 0 (no avoidance) to 6 (6 types of avoidance behaviours). Independent variables (risk measures): BEG: Binswanger-Eckel-Grossman risk measure; SOEP-G(H): German Socio-Economic Panel General (Health) risk attitude; APR: Air Pollution Risk Perception. The coefficients give expected increase in log count for a one-unit increase in predictor variable. Individual covariates include cycling behaviour (cyclist type, cycling frequency), socio-demographic attributes (age, gender, education, income, ethnicity), and surveyor covariates include categorical variables for surveyor, location and time of day. Omitted categories include, Age <35, Gender = Male, Ethnicity = White, Income <£32k, Education <UG. BAMEO = Black Asian, minority ethnic + Other, UG = Undergraduate degree. All regressions use robust standard errors. Significance levels reported at *** p<0.01, ** p<0.05, * p<0.1.

Table 4.10: Correlations between different risk measures

Risk measures	BEG	SOEP-G	SOEP-H	Lights	Helmet	Facemask	APRP
BEG	1						
SOEP-G	0.164 **	1					
SOEP-H	0.106	0.651 ***	1				
Lights	-0.070	-0.031	0.070	1			
Helmet	0.057	0.044	-0.101	0.380 ***	1		
Facemask	-0.015	0.110	0.087	0.259 **	0.045	1	
APRP	-0.030	0.162 **	0.051	0.113	0.086	0.461 ***	1

Notes: BEG: Binswanger-Eckel-Grossman risk measure; SOEP-G(H): German Socio-Economic Panel General (Health) risk attitude; Lights, Helmet and Facemask: rating of importance of item in a cycling safety kit; APRP: Air Pollution Risk Perception. The table reports pairwise correlation coefficients between variables. Pearson correlation coefficients are displayed for pairs between the following variables; SOEP-G and SOEP-H risk attitudes and APRP (they are treated as continuous variables, as their range is at least as large as 10). Polychoric correlations are reported for pairwise correlations between ordinal variables, BEG risk preference, Lights, Helmet, and Facemask. Polyserial correlation coefficients are reported for pairwise correlations between a 'continuous' and ordinal variable (e.g. between BEG and SOEP-G variables). Significance levels reported at *** p<0.01, ** p<0.05, * p<0.1.

Figure 4.1: Distribution of responses for risk-taking while cycling: By behaviours

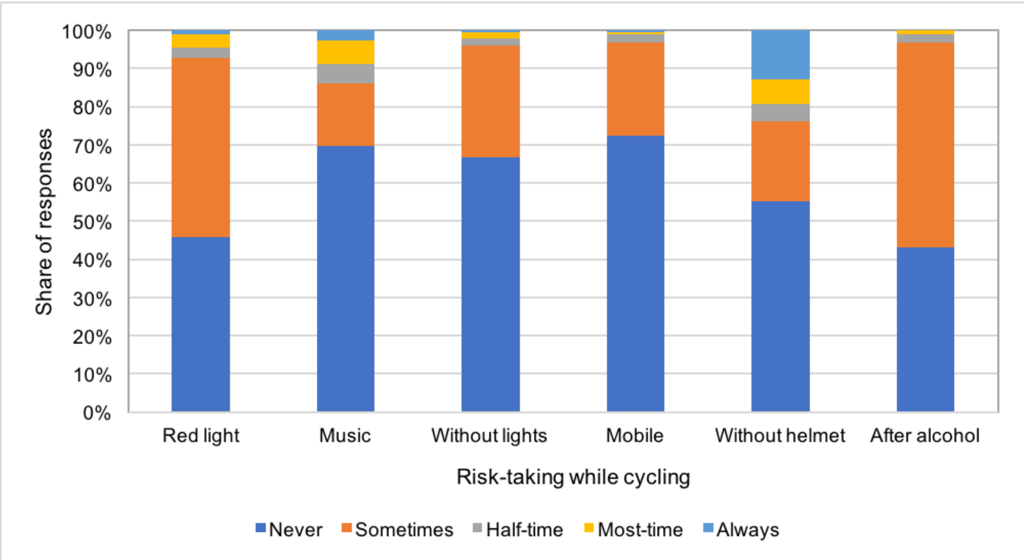


Figure 4.2: Distribution of responses for risk-taking while cycling: All behaviours (aggregate)

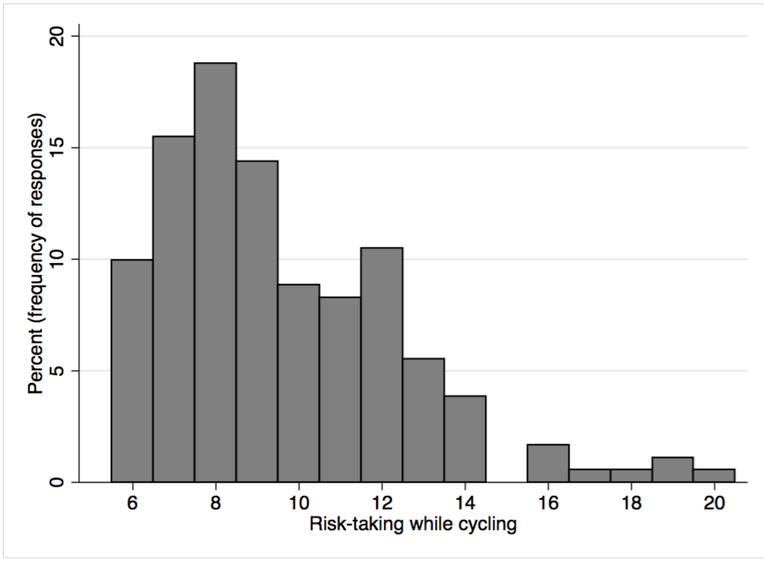


Figure 4.3: Distribution of responses for air pollution avoidance: By behaviours

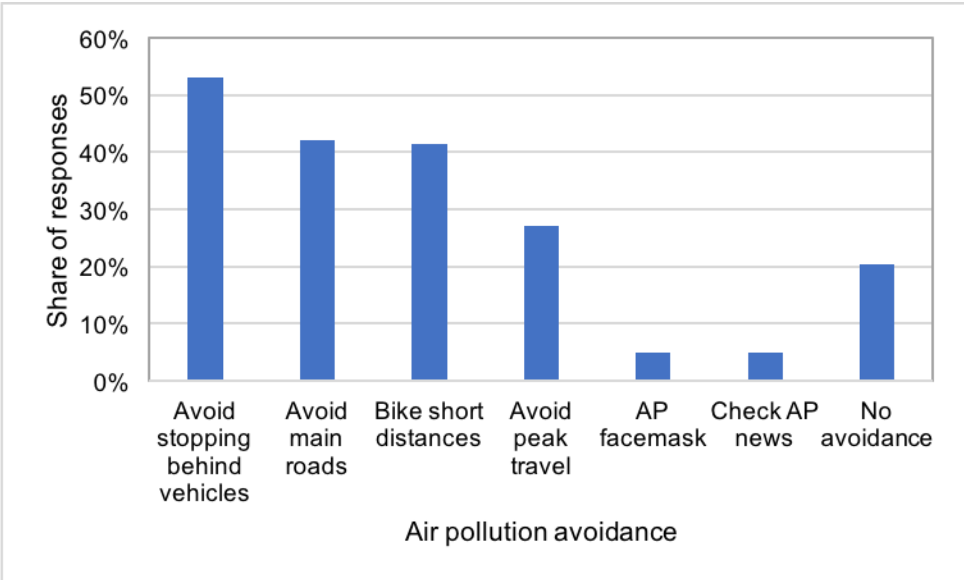
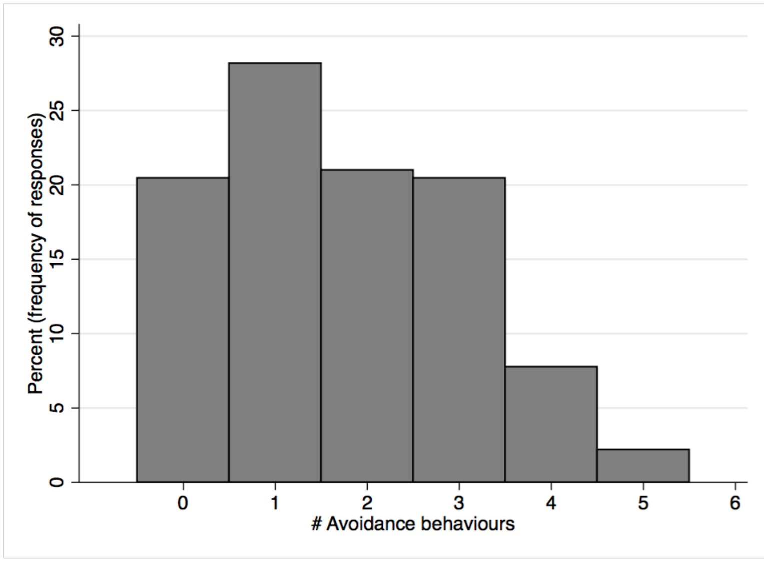


Figure 4.4: Distribution of responses for air pollution avoidance: All behaviours (aggregate)



Chapter 5

Optimistic about air quality, but avoiding polluted air? Unpacking the effects of social norm messages

5.1 Introduction

Traffic-related ambient air pollution is a life and death problem in cities worldwide. Over 80% of people in urban areas lived in places where air quality levels were deemed harmful by the World Health Organization and urban pollution levels increased by 8% annually during 2008 to 2013 (WHO, 2016). Higher air pollution is linked to the increased risk of traffic-accidents (Sager, 2016) and reduced cognitive functioning and performance (Ebenstein et al., 2016; Clifford et al., 2016), apart from increased morbidity and mortality risk.[1] Individuals can undertake short-run avoidance strategies to reduce exposure to toxic pollutants and particulates. Examples include reducing time spent outdoors on polluted days, or changing travel behaviour on-route by using segregated side-walks or reducing travel speed if cycling or running, and investing in defensive goods like anti-pollution facemasks, anti-asthmatics, or other medication if going outside is unavoidable (Giles and Koehle, 2014; Bigazzi et al., 2016; Deschênes et al., 2017).

As these avoidance strategies have direct implications for individual welfare (Zivin and Neidell, 2013), encouraging avoidance through informational strategies is an increasingly important policy lever deployed by governments. The small but essential set of studies that analyse avoidance behaviour explore how informational alerts reduce time spent outdoors (Zivin and Neidell, 2009; Janke, 2014). There is limited evidence about other behavioural strategies that could be used in public information campaigns. This reflects the lacuna in our understanding about the avoidance strategies adopted by individuals when going outside in unavoidable and the psycho-social factors underpinning these decisions.

This paper aims to address this gap by exploring the prospect of employing social norms in informational interventions to encourage avoidance. Social norms are the customary expectations, beliefs or rules governing behaviour, within a social group, to which group members try to conform (Young, 2015). Some prominent studies suggest that referencing social norms in informational interventions can change behaviour in a wide variety of contexts including driving safety (Linkenbach and Perkins, 2003; Lawrence, 2015), energy, water and other conservation behaviours (Allcott, 2011; Ferraro and Price, 2013; Goldstein et al., 2008; Cialdini et al., 2006; Dolan and Metcalfe, 2015), voter turnout (Gerber and Rogers, 2009), retirement savings (Beshears et al., 2015), and antibiotics

[1]Adverse health effects include cardiovascular, pulmonary, and respiratory diseases, including stroke, impaired lung function, asthma and cognitive function (Guarnieri and Balmes, 2014; Hoek et al., 2013; Power et al., 2011). Short-term effects include irritation of the eyes, nose, throat, and lungs (Pope III, 2000; Pope III et al., 2002). Ambient air pollution is also associated with neurological diseases such as Alzheimer's and dementia, negative affect, happiness and life satisfaction (Underwood, 2017; Zeidner and Shechter, 1988; Dolan and Laffan, 2016; Welsch, 2006; Luechinger, 2009). See Currie et al. (2014) for a review about the short-term and long-term effects of air pollution from the economics literature.

over-prescription (Hallsworth et al., 2016).

While these results are promising, there is also evidence of social norm messages failing to change behaviour in replication studies conducted in new populations or other decision-making contexts. To illustrate, Bohner and Schlüter (2014) replicated Goldstein et al. (2008)'s social norms and towel reuse experiment in Germany, but found no difference between an appeal and a descriptive norm message on towel reuse amongst hotel guests (the original study was conducted in the USA).[2] In another natural field experiment, Silva and John (2017) found no difference between an informative and descriptive norm email on the likelihood of students paying university fees on time. Yeomans and Herberich (2014) also found negatively-worded descriptive norms had no impact on decisions to inflate tires to improve fuel efficiency, compared to an informational control message. Thus, the types of contexts and populations in which normative social interventions may be most useful are unclear. These mixed findings also raise additional puzzles: who responds to social norms messaging and why? Are social norms messaging a useful strategy to encourage air pollution avoidance?

Thus, this study is aimed at evaluating not only whether individuals change avoidance behaviour in response to social norm interventions but also how responses may vary across different types of individuals. It builds on the data collected in the lab-in-the-field experiment reported in Paper 3 by implementing an informational intervention towards the end of the survey. In the intervention, subjects were either exposed to a persuasive, informational message about air pollution health risks in the control condition or a message augmented with social norms in the treatment condition. After this, individuals could choose between anti-pollution facemasks and an alternative prize in a lottery draw. This is a relevant avoidance behaviour because there has been a growth in the use of anti-pollution facemasks across cities globally, and it has been prescribed as an avoidance strategy for those cycling and exercising outdoors (Zhang and Mu, 2017; Ross, 2015; Giles and Koehle, 2014) The conceptual framework and interventions are explained in greater detail in the body of the paper.

There are three main contributions of this exploratory study. First, the effect of social norms messaging are considered in a new behavioural setting and sample, i.e., air pollution avoidance through the choice of face-masks amongst cyclists. There is little empirical evidence on how to persuade active travellers, like cyclists, to undertake air pollution avoidance (Giles et al., 2011), although they can be especially vulnerable to

[2]Schultz et al. (2008) and Reese et al. (2014) also failed to replicate Goldstein et al. (2008)'s experiment in Europe.

accident risk and inhale more pollutants and particulates along high traffic routes compared to those in cars (Panis et al., 2010; Zuurbier et al., 2011).[3]

Second, we explore whether making social norms salient in a message confers an additional benefit, over and above providing information on air pollution health risks and the role of face-masks in reducing exposure. This approach addresses Dolan and Metcalfe (2015)'s concern that there is limited field-based evidence that explicitly differentiates the behavioural effects of provisioning information and knowledge versus social norms. This evidence may be particularly relevant to the study context because both everyday air pollution health risks and many avoidance strategies (like avoiding busy routes) are mostly invisible. In the face of such uncertainty, it is possible that individuals look to others to learn about the 'appropriate' choice but also don't know about existing risks and avoidance options. Given this, the current study tests the impact of social norms over and above the knowledge of how to avoid air pollution.[4]

Third, keeping in mind that toxic air quality is difficult to decipher directly, the last contribution is to determine whether underlying beliefs about air quality influences responses to social norms information in systematically different ways. This builds on the growing literature about the heterogeneous behavioural effects of social norms and environmental information interventions (Ferraro and Price, 2013; Brown et al., 2017).

The main result of this paper is that individuals who held more optimistic beliefs about air quality, i.e., those who perceived air quality was better and were exposed to the social norms message, were more likely to choose facemasks in the lottery. That said, although a higher proportion of cyclists exposed to the social norms message chose face-masks, this difference is not statistically significant compared to the control condition for the whole sample. Taken together, these findings are part of an increasing body of evidence that suggests that the way normative messaging works is not as simple as first thought (Silva and John, 2017). More broadly, these findings highlight need to understand how underlying individual factors drive heterogeneity in responding to persuasive

[3]Previous work has shown that Short-run traffic-related air pollution negatively impacts cardiac autonomic function amongst urban cyclists (Weichenthal et al., 2011). But given the recent policy push towards active travel and lifestyles in cities, there is an ongoing debate about the extent to which active travellers are more or less at risk from pollution, compared to those using other modes of transport. Epidemiological studies estimate the long-term health benefits of cycling can outweigh health risks in all but the severest cases of ambient air pollution (Tainio et al., 2016; Götschi et al., 2016). The models assume that cyclists inhale more pollutants compared to non-active travellers, e.g. an inhalation factor of 3 is assumed for cyclists in most studies. But they omit the impact of short-term air pollution episodes and increased morbidity risk, both of which have adverse health and productivity impacts in the short-run (Tainio et al., 2016). Giles and Koehle (2014) note that exercise improves some of the physiologic mechanisms and health outcomes that air pollution exposure exacerbates, but identifies avoidance as a key behavioural strategy to reduce potential adverse consequences.

[4]I did not test the effect of information provision alone due to uncertainty about the final sample size.

messaging and calls for more research to establish how robust the behavioural effect of social norms are in real-world settings.

The remainder of this paper is structured as follows. The next section reviews the related literature, and section three lays out the conceptual framework used in the study, by discussing why social norms matter for avoidance and the role of prior beliefs about air quality. It also outlines the hypotheses for investigation. Section four describes the experimental design, and section five presents the results. Section six concludes with a discussion.

5.2 Related literature

In this section, I review the literature on existing informational interventions to promote avoidance behaviour, followed by the existing evidence on existing social norm interventions to change preventive health and active travel behaviours.

5.2.1 Air pollution information

Informational interventions are critical to empowering individuals to undertake avoidance to improve their health by reducing exposure. The assessment of everyday pollution threats is a challenging task because pollutants like PM and Nitrogen dioxide (NO_2) are unobservable to the naked eye. Moreover ambient air quality depends on variable atmospheric and environmental conditions like wind, rain, vegetation and proximity to water. In addition, ambient air quality is a complex environmental risk, involving multiple diffuse polluters, intricate chains of causality, and ambiguity about the best way to protect against poor air quality (Barker, 1974; Bickerstaff, 2004). Informational interventions can help individuals take avoidance decisions outdoors amidst uncertainties regarding the threats posed by everyday air pollution.

Governments use the standard approach of information alerts based on air quality banding to increase individual-level avoidance. Typically, they rely on forecasted air quality and advise individuals to avoid strenuous outdoor activities on high smog days. Most studies rely on cross-sectional surveys and quasi-experimental approaches, to find that alerts reduce time spent on outdoor activities (like zoo visits) (Bresnahan et al., 1997; Roberts et al., 2014; Wen et al., 2009; Zivin and Neidell, 2009; Janke, 2014) and outdoor physical activity (Noonan, 2014; Ward and Beatty, 2016; Saberian et al., 2017). Noonan (2014) found joggers and the elderly use parks less in response to smog alerts, but car drivers do not change their behaviour. Saberian et al. (2017) estimated that such alerts reduced cycle traffic by around 13% on the first day, and 1.6% on the second day. Overall, these studies suggest that information alerts on high pollution days reduce time spent outdoors, especially amongst those perceived as vulnerable, such as the elderly and those exercising outdoors. While providing useful evidence on the impact of alerts and ambient pollutant levels on avoidance, these studies do not explore avoidance strategies employed by cyclists when going outdoors is inevitable, or the psychological factors underlying avoidance decisions.

Alternately, public health advisories provide information on everyday air quality data information to give people the scientific knowledge about air pollution levels and equip them with the information to take decisions to protect themselves. This approach largely rests on the Knowledge-Deficit model, which assumes the public lacks technical and scientific information about environmental risks. Assuming agents are rational and scientific literacy is generally low, transferring technical information like air quality data from experts to the public will give the latter the informational basis to either change their behaviour and / or attitudes to emerging technologies to counter these risks (Simis et al., 2016). But growing evidence reveals that even if information provision increases awareness of the issue, it can nevertheless be relatively ineffective in producing behaviour change due to varous factors such as the complexity and mode of science communication, cognitive biases such as the availability heuristic or confirmatory bias, and / or affective reasoning (Abrahamse et al., 2005; Kollmuss and Agyeman, 2002; Sunstein, 2007). Along these lines, qualitative evidence shows that the public finds air quality information such information overly complicated, technical, or even irrelevant (Bush et al., 2001; Bickerstaff and Walker, 2003, 2001).[5]

5.2.2 Social norms

Given concerns over relying purely on the provision of scientific information to change public responses to environmental risks, subsequent efforts in both behavioural economics and psychology explore whether informational interventions are more effective at changing behaviour when they leverage social norms (Farrow et al., 2017; Nyborg et al., 2016). However, both economists and psychologists have dissimilar conceptualizations of social norms (Nyborg, 2018). In psychology, social norms tend to refer to people's beliefs about

[5]Others, like (Kahan et al., 2012) point out that public divisions over climate change stem not from the public's incomprehension of science but from a distinctive conflict of interest: between the personal interest individuals have in forming beliefs in line with those held by others with whom they share close ties and the collective one they all share in making use of the best available science to promote common welfare.

the behaviour and evaluations of group members, influence individual-level behaviour (Cialdini and Goldstein, 2004). For example, the Focus Theory of Normative Conduct distinguishes between descriptive norms (what most people do) and injunctive norms (what people ought to do). The Theory of Planned Behaviour also defines norms as social norms as the subjective beliefs about the expectations of others which can exert effects on an individual's behaviour (Ajzen, 1985, 1991). Following a social norm may be linked to conformism (i.e., a wish to fit in by being or acting like others), as an indication of the behaviour's individual pay-offs and / or social or moral appropriateness.

Psychologists also often note that descriptive and injunctive norms need not coincide, and a given situation may contain multiple (at times conflicting) norms. Given this, there is a consensus that social norms can influence behaviour when they are activated or made salient through channels like persuasive messaging (Cialdini et al., 1990; Cialdini and Goldstein, 2004). As noted by Dolan et al. (2012), messages that make social norms salient may influence behaviour through both conscious and unconscious processes: individuals may either learn about the appropriate course of action, update beliefs and change behaviour, or conversely, they may have no recollection of conforming to the norm or the choices of others, because they act 'automatically' instead.

But social norm messages may be ineffective if descriptive norms highlight that many people do not follow social norms and get away with their non-adherence (Cialdini et al., 2006). Additionally, interventions informing people that they behave better than average can also result in a worsening of behaviour, as exemplified by energy and water conservation studies (e.g. in Allcott (2011) and Schultz et al. (2007)). Consequently, there is a growing consensus in the psychology literature that aligned normative messages, where both high group involvement (descriptive norm) and group approval (injunctive norm) are salient, elicit stronger behaviour shifts in the desired direction (Hamann et al., 2015; Van Der Linden, 2015; Allcott, 2011; Schultz et al., 2008; Cialdini et al., 2006).[6]

In economics, Nyborg et al. (2016) define a social norm as 'predominant behavioural pattern within a group, supported by a shared understanding of acceptable actions, and sustained through social interactions within that group' (also see Ostrom (2000)). This implies that a social norm has to be both descriptive and injunctive, as demonstrated theoretically in Benabou and Tirole (2011). From a game theoretic standpoint, a social norm typically apply to some behaviour that is self-enforcing or constitutes the group equilibrium, because people want to adhere to the norm if they expect others to do so

[6]But there are also studies failing to establish this: for example, Kormos et al. (2015) found descriptive normative information did not affect non-commuting behaviour but had a positive effect on commuting behaviour, contrary to the 'boomerang' effect.

(Young, 2015). As noted by Nyborg (2018), if someone believes that the majority of guests staying in her hotel room before her reused their towels, reusing one's towel would not necessarily be defined as a social norm in the game-theoretic sense, but it would count as a social norm in the Focus theory of Normative Conduct in social psychology. This is because it is common but not necessarily generally viewed as more acceptable than the alternatives, i.e., opting for a clean hotel towel in a context where this appears to be usual default choice.

In addition, social norms need to be at least partly enforced through extrinsic social forces such as (dis-)approval, inclusion, exclusion or social sanctions or rewards within the group. Thus economic models pay special attention to the role of social sanctions and rewards in enforcing norm-based behaviours (Nyborg, 2018; Young, 2015; Benabou and Tirole, 2011; Akerlof and Kranton, 2000). [7] The literature on social norms in coordination games or cooperation over shared public and common pool resources typifies this approach (Nyborg, 2018; Ostrom, 2000; Bowles and Gintis, 1998). The application of social norms to self-protective and / or preventive health behaviours in economics is rather limited in comparison.[8]

In the case of preventive health behaviours, studies (predominantly from psychology) have remarked that the adherence to social norms - even at a personal cost - can be associated with higher chances of survival and safety-enhancing functions (Griskevicius et al., 2006; Maner et al., 2005). Individuals can be especially susceptible to social influence and situational cues for self-protection and disease avoidance because following others while personally uncertain, can often lead to better and more accurate decision making (Deutsch and Gerard, 1955; Cialdini et al., 1990; Griskevicius et al., 2006, 2008). There is also evidence that individuals often overestimate the prevalence of many undesirable behaviours (and underestimate the prevalence of healthy behaviours) (Borsari and Carey, 2003; Prentice and Miller, 1993). This literature on 'pluralistic ignorance' shows that individuals who assume their attitudes about specific normative behaviours are different from others - whereas most people share the same beliefs - leading them to underestimate the extent of healthy behaviours (Prentice and Miller, 1996). In this way, people can inadvertently behave in ways that endorse erroneous or unhealthy norms, because of (mis-)perceptions about how people behave. Thus, when the appropriate course of preventive action is uncertain, social norm messages can make the avoidance of others

[7] From this perspective, Nyborg (2018) notes that certain actions like abstaining from littering when alone and unobserved in the wilderness, implies following an internalized moral norm rather than a social norm, due to the lack of social enforcement.

[8] (Nyborg and Rege, 2003) is an excellent exception, as they examine the evolution of social norms around considerate smoking behaviour (which is a risky health behaviour) from the introduction of a no smoking regulation.

‘known’ or publicly observable (i.e., descriptive norm), and clarifies people’s perceptions that self-protection is socially appropriate behaviour (i.e., injunctive norm).

Current evidence on how social norms messaging impacts preventive health and sustainable travel behaviours is mixed. Studies largely rely on behavioural intentions, self-reported and observational data from university staff and students, although natural field experiments are increasingly common.[9] Few studies consider how social norms impact preventive behaviour while travelling. In early field evidence on the topic, Linkenbach and Perkins (2003) reported results from a social media campaign to encourage seatbelt use in the USA. They found that self-reported seatbelt used increased after the campaign: in 2000, 77.6% of those interviewed reported wearing a seatbelt at least 90% of the time, which went up to 82.6%, after the campaign. While promising, it is difficult to conclude that the effect was causally attributable to the social norms campaign, as the intervention was not randomised, and the study relies on before and after data. More recently, in an observational study, Lawrence (2015) used a pre-post design to study phone-related distracted driving, which was directly observed. Strong and weak injunctive norms were displayed on signboards by the gates of a university campus, where only the former made social disapproval explicit (‘97% of Dukes disapprove when you text and drive’ versus ‘Please don’t text and drive’). She found that the strong injunctive norm-framing reduced phone-related distracted driving, but that the weak injunctive norms condition had no behavioural impact. That said, the effects of the strong-injunctive norms condition washed out two weeks after the study because phone use was not significantly different from the pre-intervention period.

In the domain of sustainable transport behaviour, Yeomans and Herberich (2014) found negatively-worded descriptive norms had no impact on decisions to inflate tires to improve fuel efficiency compared to an informational control message, in a natural field experiment. Kormos et al. (2015) also found descriptive norm information had no effects on total transportation behaviour of a sample of university students and staff, in a field experiment with self-reported data. But they reported that the amount of sustainable transportation use (e.g., bus, carpool, ride-share, cycling, or walking) relative to private vehicle use increased as the proportion of people stated in the descriptive norm increased across experimental groups (especially amongst students).

[9] I focus on preventive and travel behaviours in this review, as it is beyond the scope of the study to undertake an exhaustive investigation and refer the reader to Miller and Prentice (2016) and Farrow et al. (2017) for some recent reviews of how social norm messaging has been applied to health and risk-taking behaviours like alcohol and drug consumption, and environmental behaviours.

There is also related work on how social norm messages impact choices to exercise. Burger and Shelton (2011) saw a decline in elevator use among people exposed to the descriptive norm sign in university campus locations, measured through direct observation. Priebe and Spink (2015) use a pre-post experimental design, where a sample of office workers was randomly assigned to receive email messages containing descriptive norms about co-workers' behaviour. They found that those who received descriptive norm emails about co-workers' lower sedentary behaviour and greater stair use and walking, reported decreasing their own sitting time while increasing stair use and walking at the office.

A small but growing number of studies explore how social norm messaging encourages healthier food consumption. Croker et al. (2009) found normative information increased intentions to consume fruits and vegetables amongst men, but not women, based on self-reported survey data from home-based in-person interviews in the U.K. Staunton et al. (2014) found no effect of injunctive norms on intentions to eat healthily amongst Australian university students but found a negative effect when negative descriptive norms were salient. Finally, in a natural field experiment, Thorndike et al. (2016) found no difference in the proportion of 'green' items bought from a hospital cafeteria, between American hospital employees receiving a monthly letter with social norms feedback, and a control condition without any contact. While the rate of green purchases was higher in another treatment group receiving a monthly social norms feedback plus a small financial incentive, behaviour reverted to the baseline levels after three months.

The current study adds to the literature in the following ways. First, it extends the research on social norm messaging to a new behavioural context, i.e., preferences for face-masks amongst urban cyclists. By doing so, it moves beyond the university campus and student sample into a field setting. Second, the study measures the revealed preference for face-masks, by using an incentive-compatible task, as explained in the experimental design section. The current study attempts to address extant concerns that about drawing inferences from behavioural intentions directly to choice, as demonstrated by the literature on the intention-behaviour gap (Sheeran, 2002). Bridging this gap may be especially challenging in the domain of physical activity: Rhodes and Bruijn (2013) assessed concordance/discordance of physical activity intention and behaviour in a meta-analysis, and found the intention-behaviour gap at 48%. They noted that the discordance is from intenders who do not act. In light of this, studying revealed choice is arguably complementary to studies measuring observed and self-reported behaviour, and behavioural intentions. Lastly, as seen from the literature, e.g. in Yeomans and Herberich (2014), it is not always clear the messages with social norms change behaviour compared to informational messages. Thus, the current exercise also addresses the need for more empirical evidence about the comparative benefits of using social influence messages versus persuasive, informational messages, to study what works and what doesn't (Dolan and Metcalfe, 2015). It also addresses the question of why treatment effects may be mixed by considering the impact of underlying beliefs about air quality, as discussed in the following section.

5.3 Hypotheses

Based on the literature reviewed in the previous section, I consider two hypotheses to be tested in this paper. The starting point of the analysis is that health risks from poor air quality are often unknown or uncertain to people, or they remain inattentive to them, although self-protection against poor quality air is desirable, at least in the short run while large-scale improvements in air quality occur. People may also be unaware of the instrumental value of facemasks to reduce exposure to poor quality air. Thus in the control condition, individuals are presented with information on air pollution health risks and facemasks. However, messages augmented with social norms may be more effective at inducing air pollution avoidance compared to basic information provision. Individuals may be more responsive to social norm messaging if it provides new information on individual payoffs from self-protection or possible self-protection strategies (or call people's attention to the same) or through conformism (Deutsch and Gerard, 1955; Allcott, 2011; Nyborg, 2018).[10] Thus, the first hypothesis to be tested is as follows:

Hypothesis I: Subjects exposed to informational messages augmented with social norms (treatment condition) are more likely to choose facemasks to protect against air pollution than subjects exposed to the informational message without social norms (control condition), i.e., there is a positive treatment effect.

It is possible that the impact of the information interventions that make health risks salient may vary across individuals based on underlying perceptions of air quality. Perceived air quality is an integral cognitive component of the perceptual experience of air pollution, which in turn is critical for shaping public attitudes and behaviour to protect against poor air quality. The Protection Motivation Theory suggests people first appraise health threats from poor environmental quality and then consider self-protective behaviours to manage the threat (Rogers, 1975; Lazarus, 1968). Similarly, the Health Belief Model proposes people are more prone to act if they believe they are more vulnerable

[10] Even if there is an injunctive norm to protect one's health, there may not be a widespread self-protective behaviour which is observable to that effect - which arguably implies a weak descriptive norm and therefore limiting the role of social sanctioning. Note that the distinct effect of each of the pathways, i.e., new information on individual payoffs or social / moral appropriateness of air pollution avoidance or conformity cannot be disentangled in the current study design, as discussed in the following section.

to adverse health outcomes from poor environmental quality (Rosentock, 1974). Higher ambient pollution levels are linked to higher air pollution avoidance (Zivin and Neidell, 2009; Janke, 2014; Saberian et al., 2017) and the purchase of facemasks in urban centres (Zhang and Mu, 2017; Sun et al., 2017). Given this, individuals who are pessimistic about air quality, i.e., they perceive air quality is poor, may be more influenced by the social norm message.

Conversely, it is possible that those who hold optimistic beliefs about air quality are more likely to revise their beliefs upon receiving information about health risks, and are more likely to take self-protection.[11] Along these lines, a field experiment by Brown et al. (2017) found that households who held initially optimistic beliefs about water quality (i.e., they perceived water quality was higher at the baseline), increased their short-term demand for water purification products after being informed that water quality was poor (also see Hamoudi et al. (2012) and Jalan and Somanathan (2008)). In light of this, it is possible that individuals who hold optimistic beliefs about air quality may be more prone to change their beliefs and behaviour in response to messages with social norms, compared to those who are already pessimistic. Social norm messages may draw attention to how avoidance is socially approved, as previously discussed. Moreover, as noted by Frank (2007), people tend to rely more on their social groups for sources of information about medical and health goods and services, and it is likely that higher weight is placed on new information coming from these familiar sources.

Given these two divergent possibilities, the direction of the interaction effect is an open empirical question. Also, I am currently unaware of any studies that have experimentally examined if the effects of social norm messages elicit heterogeneous treatment effects based on perceived air quality measured before the intervention. Thus, the following null hypothesis is investigated:

Hypothesis II: There is no difference in the likelihood of choosing face-masks amongst cyclists who are exposed to the aligned social norms message based on their prior beliefs about perceived air quality, i.e., there is no heterogeneous treatment effect based on perceived air quality.

[11] Other studies which have explored how information effects are heterogeneous consider the role of baseline characteristics like pre-treatment water and energy resource use (Allcott, 2011; Ferraro and Price, 2013), and consumer's tastes and socio-demographic characteristics like the degree of environmentalism and wealth (Costa and Kahn, 2013; Ferraro and Price, 2013) See Ferraro and Hanauer (2014) for a recent review.

5.4 Experimental design

5.4.1 Study context: Air pollution, facemasks, and cyclists in London

Air pollution in the UK has been recognised as a 'public health emergency' (EFRA, 2016). An estimated 59% of the U.K. population lives in areas where the level of air pollution is above the legal limits by some estimates (Laville, 2017). Recent assessments showed nearly all diesel cars emit far higher levels of NO_x on the road, than permissible in laboratory tests (DFT, 2016). Poor air quality is becoming a salient issue for the public after the government lost a series of court cases for failing to protect citizens from ambient air pollution. Anecdotal evidence and media coverage suggest that cyclists in London increasingly use facemasks to protect themselves against air pollution (Ross, 2015; Batchelor, 2017). Facemasks are recommended for those exercising in poor quality air (Giles and Koehle, 2014), and the consequent health benefits have been demonstrated amongst populations vulnerable to cardiovascular problems (Langrish et al., 2012, 2009).[12] There is empirical evidence on the increasing popularity of facemasks amongst active commuters and urban residents (Zhang and Mu, 2017; Sun et al., 2017; Ban et al., 2017). Finally, facemasks have some useful properties for this study's purpose: they are unambiguously linked to poor air quality and not conjoint environmental stressors such as noise pollution or noxious odours. Compared to other transitory avoidance strategies which are not directly revealed in markets (e.g., reducing travel speed), face-masks incur a measurable monetary cost, and their uptake can be directly measured by recording purchasing decisions in an experimental survey.

5.4.2 Participants

The study was held at the Prudential Ride London festival held during 28-31 July 2017. This annual three-day cycling festival has numerous events for professional and amateur cyclists, and the public. It offered a unique opportunity to access a sample of cyclists of different types and abilities, including commuters, recreational cyclists, as well as those interested in cycling. A random ballot determined event participation and spectators could attend cycling- themed festivities with their families. Subjects were recruited through convenience sampling. Surveyors were stationed at fixed locations in the festival zones and directly approached potential participants.[13] Participants were told that the study was about cycling in London and air pollution, that it would incur a time commitment

[12]For instance, Langrish et al. (2009) found that wearing an anti-PM facemask reduced personal exposure by up to 96.6% in a field trial in Beijing.

[13]See Appendix H for further details and field notes on data collection.

of around 10 to 15 minutes, and that they could win a prize in a lottery draw for their participation. They could participate if they were residents in the Greater London Area, cycled in London for either recreation, commuting, or both, and were over 18 years of age. After the surveyor entered affirmative responses to these screening questions, electronic tablets were handed to the participants, who completed the remainder of the survey alone. A total of 188 responses were initially gathered, and the final sample consisted of 181 observations, after screening out incomplete and interrupted responses. Most subjects were 35-54 years old (50.83%), male (66.30%), white (76.80%), with a reported household income of over £64,000 (41.96%), and at least an undergraduate degree (48.07%). This roughly mirrors the socio-demographic profile of London and UK cyclists in more representative surveys (Aldred et al., 2016; Steinbach et al., 2011; TFL, 2016).

5.4.3 Procedure

After the consent form, a preamble asked subjects to read the questions carefully, and to answer truthfully and by themselves, to promote clarity about the survey protocol and tasks. Then, subjects responded to questions on cycling and air pollution.[14] The question order was randomized to mitigate ordering and anchoring effects. Following this, subjects saw either the control or treatment message, both of which consisted of a single page of textual information with graphical illustrations. The computer program randomly assigned subjects to either the control or treatment conditions, unbeknownst to the surveyor, thus using a double-blind experimental protocol. After this, subjects could decide whether to select a facemask for a prize in a lottery draw, as explained below. The experimental survey concluded with questions on socio-demographic attributes and the lottery draw. Surveyors were available to clear any doubts but took care not to look at the control or treatment conditions, comment on air pollution, or facemasks.

5.4.4 Interventions and variables

Figures 5.1a and 5.1b present snapshots of the control and treatment messages.

Information message (control condition, N = 90): Subjects were exposed to a persuasive, informational message about air pollution in London, the health consequences, and risks for cyclists, and facemasks. The information was taken from an article

[14] The survey also included measures of stated and incentive-compatible risk attitudes, cycling frequency, risk-taking while cycling, and types of avoidance behaviour which are discussed in Paper 3. The effect of the subjects answering these questions on their subsequent choice behaviour cannot be ruled out, thus should be kept in mind while examining the results.

published by the GLA (2017) and supplemented with information from the London Air Quality Network advice page (LAQN, 2017). Both sources were included to increase message credibility, as previous work notes that public mistrust about air quality and health information is a behavioural barrier (Bickerstaff and Walker, 2001). Two graphical illustrations were included to capture attention - one to illustrate poor air quality and traffic pollution, and another to illustrate a cyclist wearing a facemask. Beneath the pictures was an informational tip written in bold red text, that using facemasks can reduce pollution exposure and improve health (supplementary materials).

Social norms message (treatment condition, N = 91): Subjects were exposed to the same informational message, appended with information on aligned social and descriptive norms, and graphical illustrations. The textual normative message (printed in bold red font) read, 'Please don't leave yourself unprotected while breathing toxic air. An increasing number of cyclists are using facemasks to protect themselves. Furthermore, 90% of Londoners think air pollution is a big problem requiring further action'. This aligned social norms message has both an injunctive norm and descriptive norms component.

The injunctive norm component is: 'Please don't leave yourself unprotected while breathing toxic air'. This is a negatively worded injunctive norm ('Please don't') because previous experimental evidence found that negatively worded injunctive norms are better at capturing attention and has a stronger impact on behaviour (Baumeister et al., 2001; Cialdini et al., 2006).

Two descriptive norms were used, namely: 'An increasing number of cyclists are using facemasks to protect themselves. Furthermore, 90% of Londoners think air pollution is a big problem requiring further action'. This format differs from descriptive norm messages typically used (e.g. 97% of the reference group undertake the social norm) because of the lack of publicly available and reliable data on face-mask use or purchase amongst cyclists in London and preference to not use deception in the manipulation. Given this, the descriptive norm used in this paper has two sub-components. The first descriptive norm is 'An increasing number of cyclists are using facemasks to protect themselves', which is used to draw attention to the self-protection of the relevant reference group of cyclists. This also follows Cialdini et al. (2006), who use 'an increasing number' rather than stating a majority figure.

The second descriptive norm is 'Furthermore, 90% of Londoners think air pollution is a big problem requiring further action' (this is taken from GLA (2017)). This second descriptive norm was added because previous studies have noted that many who cycle in London do not identify as 'cyclists' and find the identity label less appealing (e.g., in Steinbach et al. (2011). More broadly, the first descriptive norm is a local norm and the second a global norm, going by Goldstein et al. (2008) who define provincial or local norms, as 'the norms of one's local setting and circumstances' (for example, hotel guests in the same room as the subject or cyclists use of facemasks in this experiment) and global norms as the norms of an individuals less immediate surroundings (i.e., hotel guests in the hotel itself or Londoners in this experiment).

To summarise, the social normative message used aligned injunctive, local and global descriptive norms. The same graphical illustrations used in the control condition are also used in the treatment condition. But the picture of the cyclist was modified such that she made a thumbs-up gesture to signal social approval, illustrating the injunctive norm. Besides this, there were three more illustrations of cyclists wearing facemasks to make evident the descriptive norm.[15]

Perceived air quality (pre-treatment): To minimise the cognitive burden and to factor in time constraints, a single item measure was used to measure Perceived Air Quality in London (PAQL), modified from the Environmental Health component of the Perceived Residential Environment Quality Indicators (Bonaiuto et al., 2003). Subjects could report how much they agreed with the statement 'The air quality in London is good', using a 7-point Likert scale from 'Strongly disagree' (0) to 'Strongly agree' (7). The mean and median PAQL score were 1 and 1.33.

Facemask choice (behavioural outcome measure): After subjects read the information page, they were led to a page presenting them with the choice task. They could either choose an anti-PM facemask for urban cyclists worth £40, or a voucher for cycling goods worth the same amount or to opt-out of the lottery draw. It was explicitly stated that the voucher could not be redeemed for a facemask. The choice order was randomised to mitigate order effects. Immediately after subjects chose their preferred prize, they were asked to indicate the main barriers to using facemasks as a manipulation check (discussed in the following section in greater detail). The list of options was identified from the pilot stage. The outcome variable of interest was binary and took the value of 1 if the subject chose the facemask for the prize draw, and 0 otherwise.

Payment and lottery: After subjects completed the experimental survey, they read instructions for the prize draw and handed back the tablet to the surveyor. Subjects had

[15] As noted previously it was decided not to have a control group that received no message because of the uncertainty about the number of responses that would be obtained in the field. Thus, the current design cannot reveal whether social norms message would have had a positive effect on the uptake of facemasks relative to a group which saw no message.

to pick a number between 1 and 50 for the surveyor. After this, they were offered a bag of tokens, labelled 1 to 50, from which they could pick one token. If the token number matched the number vocalised to the surveyor, the subject won the draw. Upon winning, subjects had to input their email address, to obtain their chosen prize. Thus, only a subset of participants received their choice, and everyone had an equal 1-in-50 chance of winning the prize draw.

5.5 Results

The treatment is defined as being 'exposed to social norms message' for the whole sample (N=181). With perfect randomisation, the difference between the control and treatment groups yields the Average Treatment Effect (ATE) of the normative message for the entire sample. There was some attrition, as 17 subjects chose to not participate in the prize draw. Given this, we also considered the sub-sample who opted into the prize draw as the 'treated' population (N=164). In this sub-sample, we anticipated that differences in the uptake of facemasks between the control and treatment group of the sample of 'treated' subjects should yield estimates of the Average Treatment Effect on the Treated (ATT). As both populations are of theoretical interest, results on the ATE and ATT are reported in the following subsections. There is balance on covariates between the control and treatment conditions (including pre-treatment subjective variables and individual attributes, and survey variables such as location and surveyor, Appendix E, Tables E.1 and E.2).

5.5.1 Treatment effects: Social norm messages

To test Hypothesis I of a positive treatment effect of the social norms message on the choice of facemasks in the lottery draw, the analysis proceeds in two steps. First, the Pearson's chi-squared test of association is used, as both the explanatory and outcome variables are categorical. Then, a binary logistic regression analysis is used to examine the probability that subjects chose the facemasks when exposed to the normative message. The main advantage of the latter technique was that we could control for potential surveyor and location fixed effects, through the addition of surveyor and location dummies in the regression model.

Figures 5.2 and 5.3 display the proportion of subjects who chose the facemask for the control and treatment conditions for the whole sample (ATE, N = 181) and the treated sample (ATT, N = 164). The empirical pattern was in line with Hypothesis I because a higher share of cyclists exposed to the normative message chose the facemask. However, the difference was not statistically significant. For the whole sample, 28.89% chose the facemask in the control group, versus 38.46% in the treatment group (chi-square with one degree of freedom = 1.856, p = 0.173). In the sub-sample who opted to participate in the prize draw, 31.71% of the subjects chose the facemask in the control group, versus 42.68% of the subjects in the treatment group (chi-squared = 2.114, p = 0.146).

[Figures 5.2, Figure 5.3 and Table 5.1]

The results of the logistic regression models are consistent with the chi-squared test. The independent variable (treatment dummy) is regressed on the binary outcome variable (choice of facemask). Table 5.1 presents the coefficients on the treatment variable, with and without survey dummies (for surveyor and location), for the whole sample, and those who opt into the prize draw. The logit coefficients on the treatment dummy, represent the ATE in model (1) (b = 0.431, S.E. = 0.318, z = 1.36, p = 0.175) and model (2) which includes survey dummies (b = 0.410, S.E. = 0.325, z = 1.26, p = 0.206). Similarly, the ATT shown in model (3) (b = 0.472, S.E. = 0.326, z = 1.45, p = 0.148) and (4) (b = 0.468, S.E. = 0.332, z = 1.41, p = 0.159), show a positive difference which is not statistically significant. Thus, both the chi-squared test and binary regression results yield no empirical support for Hypothesis I.

Robustness checks: As an additional robustness check, the sample is restricted to responses collected at the main survey location (N = 129). The treatment effect is positive and significant at the 10% level in the chi-squared test of association (chi-squared = 2.7613, p = 0. 097), and the logit regression (b = 0.641, S.E. = 0.388, z = 1.65, p = 0.099). Once survey dummies are added, the coefficient on the treatment dummy is not significant at conventional levels (b = 0.611, S.E. = 0.393, z = 1.55, p = 0.120). One conceivable explanation for the lack of a treatment effect is that subjects did not read the message properly or did not find the normative message persuasive. Three manipulation checks were performed to address this concern. As the treatment message contained aligned descriptive and injunctive norms, it was hypothesised that fewer subjects would select 'No-one else wears facemasks', and 'Embarrassing, very visible', when asked about the perceived barriers to wearing a facemask. It is also possible that subjects in the normative message group would perceive fewer overall barriers to wearing a facemask than in the control group if the social norms message was more persuasive. The results showed that a lower proportion of subjects chose 'No-one else wears one' in the treatment condition compared to the control and that the difference is significant at the 10% level (chi-squared with one degree of freedom = 3.267, p-value = 0.071). The number of perceived barriers chosen is also lower in the treatment condition at the 5% level (t = 2.222, degrees of freedom = 179, p-value = 0.028). However, the groups did not differ in the proportion of subjects choosing "Embarrassing very visible" as a perceived barrier. By and large, these results suggest that the treatment manipulation was not ineffective.

5.5.2 Heterogeneous treatment effect: Perceived air quality

The analysis proceeds to test for heterogeneous treatment effects using logistic regressions with two-way interactions. The interaction term should be statistically significant in the regression models (e.g., in Aiken et al. (1991); Ferraro and Hanauer (2014)). In the following section, results on both the whole sample (N=181, ATE) and the restricted treated sample (N= 164, ATE), with and without surveyor and location dummies, are provided. I also plot the predicted probabilities of the interactions to facilitate the interpretation of the moderation effects.

Hypothesis II proposes that there are no heterogeneous treatment effects by baseline perceived air quality, i.e., cyclists who perceived lower air quality in London, would not be influenced any differently by normative messages, than cyclists who perceived higher air quality. The sample is divided into those which report perceived air quality above or below the sample median, and a binary dummy for the high and low sub-groups was created to differentiate between those who hold higher and lower beliefs about the air quality in London is created: it takes a value of 1 if the value falls at or above the median score of PAQL. Recall that this value is also nearly equivalent to the mean score. The low sub-group, i.e., those who believe in poorer air quality, takes the value of 0 and is the omitted category. This follows standard approaches used in literature to test for heterogeneous treatment effects in field experiments (e.g. in Brown et al. (2017); Ferraro and Price (2013); Ferraro and Hanauer (2014)). As both the treatment dummy and moderator are dichotomous, the moderation analysis used a 2 x 2 design.

[Figure 5.4 and Table 5.2]

For the whole sample without survey fixed effects, the logistic coefficients on the interaction term was positive and significant a the 10% level (b = 1.288, S.E. = 0.740, z = 1.75, p = 0.081, N = 181; Table 5.2). This result implies that the odds of choosing a facemask amongst cyclists who believe air quality was better increased by 28.8% when exposed to the normative message. When survey dummies were added, the size of the interaction term coefficient and significance level marginally increased and the interaction terms is positive and significant at the 5% level (b = 1.545, S.E. = 0.763, z = 2.09, p = 0.043, N = 181).

Fitted probabilities obtained from the model also illustrate this difference. Figure 5.4 shows cyclists with pre-treatment beliefs that air quality in London was better were more likely to choose facemasks compared with the control group after receiving the normative message (predicted probability = 0.537, S.E. = 0.094, z = 5.71, $p < 0.001$), whereas the choices of cyclists who believed air quality was poorer, were not markedly different compared to the control condition. The results on the interaction terms were nearly identical when the sample was restricted to those selecting into the lottery draw (b = 1.600, S.E. = 0.763, z = 2.09, p = 0.036, N = 164). In short, the fitted probabilities and odds ratios provide initial empirical support against null Hypothesis 2. For cyclists who believed air quality was higher, the odds of selecting a facemask is multiplied by 3.62 to 4.68, compared to subjects who held beliefs that air quality was poorer.

Robustness checks: Given the assignment to the treatment group was random, and there was balance on observables, the analysis excluded controls for socio-demographic variables. I check if the heterogeneous treatment effect remains significant with the addition of individual controls as a robustness check. Both the magnitude and direction of the interaction term remains qualitatively similar and is significant at the 10% for both ATE and ATT samples. The results were qualitatively similar when the sample was restricted to those perceive optimistic air quality, both with and without survey and individual controls (see Appendix E, Tables E.3 and E.4). In addition, it is possible that either risk preferences or risk perception influence the subjective perception of air quality (which may depend on information acquisition, which in turn may depend on risk). Therefore I first check whether the treatment effect interacts with BEG, SOEP-G, SOEP-H risk preferences and air pollution risk perception elicited in Chapter 4. As seen in the previous chapter, none of the risk preference measures are positively associated with the treatment effect and the interaction terms with the treatment dummy are also not statistically significant. On the other hand, air pollution risk perception is positively and signifcantly associated with the uptake of facemasks (in line with the findings of Chapter 4) but the interaction term between the treatment dummy and air pollution risk perception is not significant. I also check whether there are any three-way interaction effects between risk preferences (or perception), perceived air quality and the treatment dummy, but the effects are not statistically significant either. These results are also omitted for brevity, but available on request.

5.6 Limitations and thoughts for future research

This exploratory study is not without some limitations. In this section, I touch upon these and also try to unpack the various reasons why we fail to see a positive average treatment effect in the current study. This serves to highlight considerations for future work, and the issues are organised by the study design and context.

The lab-in-the-field experimental method is likely to afford greater generalizability than a lab experiment, given the field setting, sample population, and double-blind experimental protocol. However, external validity is threatened by the opt-in design with convenience sampling. Given average treatment effects were in the expected direction, using a larger and more representative sample could yield stronger results, and is another promising path for subsequent research.

The paper measured revealed preferences for face-masks, as opposed to a cycling voucher for the same amount. While this approach has the advantage of being incentive-compatible compared to studies using behavioural intentions or self-reported behaviour, the observed choice may be contingent on the choice set used and experimental survey setting. Measuring 'use' over time is an important consideration for future work, in the light of past evidence showing that treatment effects of social norm messages tend to wash out over the long run in some settings (e.g. in Thorndike et al. (2016); Lawrence (2015)).

Other points about the study design are also of note. I followed Cialdini et al. (2006) to use a negatively valenced injunctive norm ('Please don't. . . ') due to the possibility of stronger behavioural effects and the need to capture attention in the naturalistic field setting. This design choice was perceived as desirable keeping in mind Lawrence (2015) observed no change in phone-distracted driving with the use of weak, positively worded injunctive norms. However, proscriptive messages (i.e., what people should not do) may induce reactance. Specifically, proscriptions may be perceived as demanding and induce participants to resist conformity by opposing the behavioural request, and it is possible, that this 'attention-reactance' tradeoff may have diluted the impact of the aligned normative message on behaviour rather than strengthening it (Bergquist and Nilsson, 2016). Future work could disentangle the individual and interaction effects of different norms (namely descriptive, injunctive, personal, local and global norms), all of which of which may have a distinct impact of behaviour (e.g., in Vinnell et al. (2018)).

Social norm interventions may be less effective at changing behaviour when consumers believe their actions are less likely to improve outcomes or perceive that the preventive health behaviour is ineffective (Bandura, 2004). Both self-efficacy and perceived barriers to use are critical factors in the protection motivation and health beliefs models (Lazarus, 1968; Rosentock, 1974; Ban et al., 2017). In this regard, the efficacy of facemasks depends on the filtration system, product fit, and use behaviour, all of which are hotly debated topics according to anecdotal evidence. Moreover, using facemasks incurs high personal effort and even discomfort – 60.8% of the sample reported that discomfort was a perceived barrier to using the facemask, and 40.9% reported that using one incurred too much bother. More broadly, qualitative evidence reveals that individuals can hold persistent beliefs that the solution to air pollution lies outside the individual (on the government or big polluters), or that they are powerless to act to mitigate such a ubiquitous problem (Bickerstaff and Walker, 2001; Bickerstaff, 2004). In this case, social norms may be less influential if people feel the costs and perceived barriers to using facemasks outweigh the benefits.

Moreover, facemasks are a visually striking and conspicuous avoidance behaviour. Previous studies show people face predilections to either stand out or fit in (Griskevicius et al., 2006). As the choice of wearing a facemask makes people stand out, this could have conflicted with the social norm message which encouraged people to fit in for self-protection. Interestingly, there is no statistically significant difference in the proportion of subjects reporting 'Embarrassing, very visible' between the treatment and control conditions in the manipulation check. Investigating these inherent tensions could be an exciting line of future work.

Thøgersen (2006) proposes normative messages have more impact when strongly internalised norms are present. It is possible that air pollution avoidance is not a strongly internalised norm in this sample, but it is difficult to conclude this was the case, as personal norms were not measured. Suggestively, however, few cyclists reported undertaking avoidance strategies - only 5% of the sample report checking air pollution information, 53% report avoiding large diesel vehicles and 42% report avoiding main roads while cycling (it is unclear whether cyclists undertake these strategies for air pollution specifically, or also to avoid noise, congestion, and accident risk). Additionally, cyclists arguably produce lower emissions from their travel mode, which in turn can raise ethical questions to as to whether individuals believe that they should invest money, time and effort to avoid poor air quality. Although the current study does not address these issues, the use of random assignment presumes that the participants' pre-treatment behaviour, attitudes, personal norms, and beliefs were evenly distributed across the treatment and control conditions. Therefore, it is difficult to conclude how these individual factors affect the observed treatment effects in the current study. Importantly, these issues again present novel directions for future research.

The results suggest that pre-treatment beliefs drive variations in the effect of social norm messages, in a potentially counter-intuitive way: cyclists with more optimistic beliefs were more likely to choose facemasks in the treatment condition. This result is in line with studies on risk communication, that also show information effects vary by beliefs about water quality (Brown et al., 2017). Extending this work further, I provide new indicative evidence that normative social information may have an additional impact, over and above information on environmental quality. A limitation of the current study is that potential changes in perceived air quality were not measured after the manipulation. Thus I am unable to shed light on whether beliefs about air quality changed actually after exposure to the social norm message. Similarly, perceived severity of threats from poor air quality was also not recorded. Future work can investigate these questions in greater detail, alongside the role of other individual-level attributes that may impact information effects.[16]

5.7 Conclusion

More research is needed to understand the avoidance behaviours undertaken by individuals when going outdoors is inevitable and the psychological processes underpinning this type of decision-making. There is a growing consensus that social norms are an effective tool to shift behaviour. However, a closer look at the empirical evidence, especially on transport and preventive health behaviours, offers somewhat inconclusive results. Interrogating the robustness of social norm messages in different contexts and populations, and the underlying factors driving differences in responses across individuals can help furnish insights to advance this discussion.

This exploratory study adds to the literature, by employing a lab-in-the-field experiment to assess the impact of normative social interventions on the uptake of anti-pollution facemasks, compared to an informational control condition. I also test if treatment effects were heterogeneous based on prior beliefs about air quality. The study does not find a statistically significant impact of normative social interventions relative to the control condition, even though the proportion of cyclists choosing facemasks was higher. However, prior beliefs about air quality induce heterogeneous treatment effects, i.e., those who were more optimistic about air quality were more likely to chose facemasks, compared to those who already believed air quality was poorer when exposed to the social norms message.

The findings suggest future work could go beyond average treatment effects when interpreting the effects of social norm messages, in the spirit of Ferraro and Price (2013)

[16]Treatment effects were not heterogeneous by other covariates as described in chapter 4, including (a) air pollution risk perception (b) risk attitudes (BEG, SOEP-G and SOEP-H, attitudes to facemasks) (c) pre-treatment avoidance/use of face-mask (d) gender, age and income. The results are omitted for brevity, but available on request.

and Allcott (2011). But it goes further by making a case for researchers and policymakers to better understand underlying subjective beliefs around environmental quality as a driving force behind the heterogeneity in treatment effects. As this is exploratory work, more evidence to establish the robustness of social norm messaging to change avoidance behaviour in a field setting is a promising way forward. From a policy perspective, these findings highlight that air pollution awareness campaigns could address core beliefs about air quality and exposure, and investigate the comparative benefits of framing outreach strategies using social norms. That said, policymakers and researchers would also need to consider the welfare implications of these arising from the time and effort taken by individuals to undertake avoidance, apart from the potential psychological costs from worrying about poor air quality.

Bibliography

Abrahamse, W., Steg, L., Vlek, C., and Rothengatter, T. (2005). A review of intervention studies aimed at household energy conservation. *Journal of environmental psychology*, 25(3):273–291.

Aiken, L. S., West, S. G., and Reno, R. R. (1991). *Multiple regression: Testing and interpreting interactions*. Sage.

Ajzen, I. (1985). From intentions to actions: A theory of planned behavior. In *Action control*, pages 11–39. Springer.

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, 50(2):179–211.

Akerlof, G. A. and Kranton, R. E. (2000). Economics and identity. *The Quarterly Journal of Economics*, 115(3):715–753.

Aldred, R., Woodcock, J., and Goodman, A. (2016). Does more cycling mean more diversity in cycling? *Transport reviews*, 36(1):28–44.

Allcott, H. (2011). Social norms and energy conservation. *Journal of public Economics*, 95(9-10):1082–1095.

Ban, J., Zhou, L., Zhang, Y., Anderson, G. B., and Li, T. (2017). The health policy implications of individual adaptive behavior responses to smog pollution in urban china. *Environment international*, 106:144–152.

Bandura, A. (2004). Health promotion by social cognitive means. *Health education & behavior*, 31(2):143–164.

Barker, M. L. (1974). Information and complexity:" the conceptualisation of air pollution by specialist groups". *Environment and Behavior*, 6(3):346.

Batchelor, T. (2017). 5 best anti-pollution masks for cycling. http://www.independent.co.uk/extras/indybest/outdoor-activity/cycling/best-anti-pollution-mask-cycling-review-london-a7952771.html [Accessed: 23 January 2018].

Baumeister, R. F., Bratslavsky, E., Finkenauer, C., and Vohs, K. D. (2001). Bad is stronger than good. *Review of general psychology*, 5(4):323.

Benabou, R. and Tirole, J. (2011). Laws and norms. Technical report, National Bureau of Economic Research.

Bergquist, M. and Nilsson, A. (2016). I saw the sign: Promoting energy conservation via normative prompts. *Journal of Environmental Psychology*, 46:23–31.

Beshears, J., Choi, J. J., Laibson, D., Madrian, B. C., and Milkman, K. L. (2015). The effect of providing peer information on retirement savings decisions. *The Journal of finance*, 70(3):1161–1201.

Bickerstaff, K. (2004). Risk perception research: socio-cultural perspectives on the public experience of air pollution. *Environment international*, 30(6):827–840.

Bickerstaff, K. and Walker, G. (2001). Public understandings of air pollution: the 'localisation'of environmental risk. *Global Environmental Change*, 11(2):133–145.

Bickerstaff, K. and Walker, G. (2003). The place (s) of matter: matter out of place–public understandings of air pollution. *Progress in Human Geography*, 27(1):45–67.

Bigazzi, A. Y., Broach, J., and Dill, J. (2016). Bicycle route preference and pollution inhalation dose: Comparing exposure and distance trade-offs. *Journal of Transport & Health*, 3(1):107–113.

Bohner, G. and Schlüter, L. E. (2014). A room with a viewpoint revisited: Descriptive norms and hotel guests' towel reuse behavior. *PloS one*, 9(8):e104086.

Bonaiuto, M., Fornara, F., and Bonnes, M. (2003). Indexes of perceived residential environment quality and neighbourhood attachment in urban environments: a confirmation study on the city of rome. *Landscape and urban planning*, 65(1-2):41–52.

Borsari, B. and Carey, K. B. (2003). Descriptive and injunctive norms in college drinking: a meta-analytic integration. *Journal of studies on alcohol*, 64(3):331–341.

Bowles, S. and Gintis, H. (1998). The moral economy of communities: Structured populations and the evolution of pro-social norms. *Evolution and Human Behavior*, 19(1):3–25.

Bresnahan, B. W., Dickie, M., and Gerking, S. (1997). Averting behavior and urban air pollution. *Land Economics*, pages 340–357.

Brown, J., Hamoudi, A., Jeuland, M., and Turrini, G. (2017). Seeing, believing, and behaving: Heterogeneous effects of an information intervention on household water treatment. *Journal of Environmental Economics and Management*, 86:141–159.

Burger, J. M. and Shelton, M. (2011). Changing everyday health behaviors through descriptive norm manipulations. *Social Influence*, 6(2):69–77.

Bush, J., Moffatt, S., and Dunn, C. (2001). 'even the birds round here cough':: stigma, air pollution and health in teesside. *Health & place*, 7(1):47–56.

Cialdini, R. B., Demaine, L. J., Sagarin, B. J., Barrett, D. W., Rhoads, K., and Winter, P. L. (2006). Managing social norms for persuasive impact. *Social influence*, 1(1):3–15.

Cialdini, R. B. and Goldstein, N. J. (2004). Social influence: Compliance and conformity. *Annu. Rev. Psychol.*, 55:591–621.

Cialdini, R. B., Reno, R. R., and Kallgren, C. A. (1990). A focus theory of normative conduct: Recycling the concept of norms to reduce littering in public places. *Journal of personality and social psychology*, 58(6):1015.

Clifford, A., Lang, L., Chen, R., Anstey, K. J., and Seaton, A. (2016). Exposure to air pollution and cognitive functioning across the life course–a systematic literature review. *Environmental research*, 147:383–398.

Costa, D. L. and Kahn, M. E. (2013). Energy conservation "nudges" and environmentalist ideology: Evidence from a randomized residential electricity field experiment. *Journal of the European Economic Association*, 11(3):680–702.

Croker, H., Whitaker, K., Cooke, L., and Wardle, J. (2009). Do social norms affect intended food choice? *Preventive medicine*, 49(2-3):190–193.

Currie, J., Zivin, J. G., Mullins, J., and Neidell, M. (2014). What do we know about short-and long-term effects of early-life exposure to pollution? *Annu. Rev. Resour. Econ.*, 6(1):217–247.

Deschênes, O., Greenstone, M., and Shapiro, J. S. (2017). Defensive investments and the demand for air quality: Evidence from the nox budget program. *American Economic Review*, 107(10):2958–89.

Deutsch, M. and Gerard, H. B. (1955). A study of normative and informational social influences upon individual judgment. *The journal of abnormal and social psychology*, 51(3):629.

DFT (2016). Vehicle emissions testing programme. https://www.parliament.uk/business/committees/committees-a-z/commons-select/environment-food-and-rural-affairs-committee/news-parliament-2015/mps-demand-action-air-quality-16-17/ [Accessed: 23 January 2018].

Dolan, P., Hallsworth, M., Halpern, D., King, D., Metcalfe, R., and Vlaev, I. (2012). Influencing behaviour: The mindspace way. *Journal of Economic Psychology*, 33(1):264–277.

Dolan, P. and Laffan, K. (2016). Bad air days: The effects of air quality on different measures of subjective well-being. *Journal of Benefit-Cost Analysis*, 7(1):147–195.

Dolan, P. and Metcalfe, R. (2015). Neighbors, knowledge, and nuggets: two natural field experiments on the role of incentives on energy conservation. Technical report, Becker Friedman Institute for Research in Economics. Becker Friedman Institute for Research in Economics Working Paper No. 2589269.

Ebenstein, A., Lavy, V., and Roth, S. (2016). The long-run economic consequences of high-stakes examinations: evidence from transitory variation in pollution. *American Economic Journal: Applied Economics*, 8(4):36–65.

EFRA (2016). Mps demand urgent action to improve air quality. https://www.parliament.uk/business/committees/committees-a-z/commons-select/environment-food-and-rural-affairs-committee/news-parliament-2015/mps-demand-action-air-quality-16-17/ [Accessed: 23 January 2018].

Farrow, K., Grolleau, G., and Ibanez, L. (2017). Social norms and pro-environmental behavior: A review of the evidence. *Ecological Economics*, 140:1–13.

Ferraro, P. J. and Hanauer, M. M. (2014). Advances in measuring the environmental and social impacts of environmental programs. *Annual review of environment and resources*, 39:495–517.

Ferraro, P. J. and Price, M. K. (2013). Using nonpecuniary strategies to influence behavior: evidence from a large-scale field experiment. *Review of Economics and Statistics*, 95(1):64–73.

Frank, R. G. (2007). Behavioral economics and health economics. In Diamond, P. and Vartianen, H., editors, *Behavioral Economics and Its Applications*, pages 195–234. Princeton University Press.

Gerber, A. S. and Rogers, T. (2009). Descriptive social norms and motivation to vote: Everybody's voting and so should you. *The Journal of Politics*, 71(1):178–191.

Giles, L. V., Barn, P., Künzli, N., Romieu, I., Mittleman, M. A., van Eeden, S., Allen, R., Carlsten, C., Stieb, D., Noonan, C., et al. (2011). From good intentions to proven interventions: effectiveness of actions to reduce the health impacts of air pollution. *Environmental health perspectives*, 119(1):29.

Giles, L. V. and Koehle, M. S. (2014). The health effects of exercising in air pollution. *Sports Medicine*, 44(2):223–249.

GLA (2017). 9 out of 10 londoners say air pollution is at 'crisis' levels - poll. https://www.london.gov.uk/press-releases/mayoral/londoners-poll-air-pollution-is-at-crisis-levels [Accessed: 23 January 2018].

Goldstein, N. J., Cialdini, R. B., and Griskevicius, V. (2008). A room with a viewpoint: Using social norms to motivate environmental conservation in hotels. *Journal of consumer Research*, 35(3):472–482.

Götschi, T., Garrard, J., and Giles-Corti, B. (2016). Cycling as a part of daily life: a review of health perspectives. *Transport Reviews*, 36(1):45–71.

Griskevicius, V., Cialdini, R. B., and Goldstein, N. J. (2008). Social norms: An underestimate and underemployed lever for managing climate change. *International Journal of Sustainability Communication*, 3:5–13.

Griskevicius, V., Goldstein, N. J., Mortensen, C. R., Cialdini, R. B., and Kenrick, D. T. (2006). Going along versus going alone: When fundamental motives facilitate strategic (non) conformity. *Journal of personality and social psychology*, 91(2):281.

Guarnieri, M. and Balmes, J. R. (2014). Outdoor air pollution and asthma. *The Lancet*, 383(9928):1581–1592.

Hallsworth, M., Chadborn, T., Sallis, A., Sanders, M., Berry, D., Greaves, F., Clements, L., and Davies, S. C. (2016). Provision of social norm feedback to high prescribers of antibiotics in general practice: a pragmatic national randomised controlled trial. *The Lancet*, 387(10029):1743–1752.

Hamann, K. R., Reese, G., Seewald, D., and Loeschinger, D. C. (2015). Affixing the theory of normative conduct (to your mailbox): Injunctive and descriptive norms as predictors of anti-ads sticker use. *Journal of Environmental Psychology*, 44:1–9.

Hamoudi, A., Jeuland, M., Lombardo, S., Patil, S., Pattanayak, S. K., and Rai, S. (2012). The effect of water quality testing on household behavior: evidence from an experiment in rural india. *The American journal of tropical medicine and hygiene*, 87(1):18–22.

Hoek, G., Krishnan, R. M., Beelen, R., Peters, A., Ostro, B., Brunekreef, B., and Kaufman, J. D. (2013). Long-term air pollution exposure and cardio-respiratory mortality: a review. *Environmental Health*, 12(1):43.

Jalan, J. and Somanathan, E. (2008). The importance of being informed: Experimental evidence on demand for environmental quality. *Journal of development Economics*, 87(1):14–28.

Janke, K. (2014). Air pollution, avoidance behaviour and children's respiratory health: Evidence from england. *Journal of health economics*, 38:23–42.

Kahan, D. M., Peters, E., Wittlin, M., Slovic, P., Ouellette, L. L., Braman, D., and Mandel, G. (2012). The polarizing impact of science literacy and numeracy on perceived climate change risks. *Nature climate change*, 2(10):732.

Kollmuss, A. and Agyeman, J. (2002). Mind the gap: why do people act environmentally and what are the barriers to pro-environmental behavior? *Environmental education research*, 8(3):239–260.

Kormos, C., Gifford, R., and Brown, E. (2015). The influence of descriptive social norm information on sustainable transportation behavior: A field experiment. *Environment and Behavior*, 47(5):479–501.

Langrish, J., Bosson, J., Unosson, J., Muala, A., Newby, D., Mills, N., Blomberg, A., and Sandström, T. (2012). Cardiovascular effects of particulate air pollution exposure: time course and underlying mechanisms. *Journal of internal medicine*, 272(3):224–239.

Langrish, J. P., Mills, N. L., Chan, J. K., Leseman, D. L., Aitken, R. J., Fokkens, P. H., Cassee, F. R., Li, J., Donaldson, K., Newby, D. E., et al. (2009). Beneficial cardiovascular effects of reducing exposure to particulate air pollution with a simple facemask. *Particle and fibre toxicology*, 6(1):8.

LAQN (2017). What can i do. https://www.londonair.org.uk/LondonAir/Guide/MyActionsForOthers.aspx [Accessed: 23 January 2018].

Laville, S. (2017). https://www.theguardian.com/environment/2017/apr/22/nearly-40-million-people-live-in-uk-areas-with-illegal-air-pollution [Accessed date: 23 March 2018].

Lawrence, N. K. (2015). Highlighting the injunctive norm to reduce phone-related distracted driving. *Social Influence*, 10(2):109–118.

Lazarus, R. S. (1968). Emotions and adaptation: Conceptual and empirical relations. In *Nebraska symposium on motivation*. University of Nebraska Press.

Linkenbach, J. and Perkins, H. (2003). Most of us wear seatbelts: The process and outcomes of a 3-year statewide adult seatbelt campaign in montana. http://www.socialnormsresources.org/casestudies/montanaseatbelt.php [Accessed: 23 January 2018].

Luechinger, S. (2009). Valuing air quality using the life satisfaction approach. *The Economic Journal*, 119(536):482–515.

Maner, J. K., Kenrick, D. T., Becker, D. V., Robertson, T. E., Hofer, B., Neuberg, S. L., Delton, A. W., Butner, J., and Schaller, M. (2005). Functional projection: How fundamental social motives can bias interpersonal perception. *Journal of personality and social psychology*, 88(1):63.

Miller, D. T. and Prentice, D. A. (2016). Changing norms to change behavior. *Annual review of psychology*, 67:339–361.

Noonan, D. S. (2014). Smoggy with a chance of altruism: the effects of ozone alerts on outdoor recreation and driving in atlanta. *Policy Studies Journal*, 42(1):122–145.

Nyborg, K. (2018). Social norms and the environment. *Annual Review of Resource Economics*, 10(1):null.

Nyborg, K., Anderies, J. M., Dannenberg, A., Lindahl, T., Schill, C., Schlüter, M., Adger, W. N., Arrow, K. J., Barrett, S., Carpenter, S., et al. (2016). Social norms as solutions. *Science*, 354(6308):42–43.

Nyborg, K. and Rege, M. (2003). On social norms: the evolution of considerate smoking behavior. *Journal of Economic Behavior & Organization*, 52(3):323–340.

Ostrom, E. (2000). Collective action and the evolution of social norms. *Journal of economic perspectives*, 14(3):137–158.

Panis, L. I., De Geus, B., Vandenbulcke, G., Willems, H., Degraeuwe, B., Bleux, N., Mishra, V., Thomas, I., and Meeusen, R. (2010). Exposure to particulate matter in traffic: a comparison of cyclists and car passengers. *Atmospheric Environment*, 44(19):2263–2270.

Pope III, C. A. (2000). Epidemiology of fine particulate air pollution and human health: biologic mechanisms and who's at risk? *Environmental health perspectives*, 108(Suppl 4):713.

Pope III, C. A., Burnett, R. T., Thun, M. J., Calle, E. E., Krewski, D., Ito, K., and Thurston, G. D. (2002). Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. *Jama*, 287(9):1132–1141.

Power, M. C., Weisskopf, M. G., Alexeeff, S. E., Coull, B. A., Spiro III, A., and Schwartz, J. (2011). Traffic-related air pollution and cognitive function in a cohort of older men. *Environmental health perspectives*, 119(5):682.

Prentice, D. A. and Miller, D. T. (1993). Pluralistic ignorance and alcohol use on campus: some consequences of misperceiving the social norm. *Journal of personality and social psychology*, 64(2):243.

Prentice, D. A. and Miller, D. T. (1996). Pluralistic ignorance and the perpetuation of social norms by unwitting actors. In *Advances in experimental social psychology*, volume 28, pages 161–209. Elsevier.

Priebe, C. S. and Spink, K. S. (2015). Less sitting and more moving in the office: Using descriptive norm messages to decrease sedentary behavior and increase light physical activity at work. *Psychology of Sport and Exercise*, 19:76–84.

Reese, G., Loew, K., and Steffgen, G. (2014). A towel less: Social norms enhance pro-environmental behavior in hotels. *The Journal of Social Psychology*, 154(2):97–100.

Rhodes, R. E. and Bruijn, G.-J. (2013). How big is the physical activity intention–behaviour gap? a meta-analysis using the action control framework. *British journal of health psychology*, 18(2):296–309.

Roberts, J. D., Voss, J. D., and Knight, B. (2014). The association of ambient air pollution and physical inactivity in the united states. *PLoS One*, 9(3):e90143.

Rogers, R. W. (1975). A protection motivation theory of fear appeals and attitude change1. *The journal of psychology*, 91(1):93–114.

Rosentock, I. (1974). The health belief model and preventive health behaviour. *Health Education Monogram*, 2:354–386.

Ross, U. (2015). Anti-pollution cycling masks tested. https://www.theguardian.com/environment/bike-blog/2015/oct/07/avoiding-pollution-on-bike-we-test-cycling-anti-pollution-masks-respro-totobobo-bi [Accessed: 23 January 2018].

Saberian, S., Heyes, A., and Rivers, N. (2017). Alerts work! air quality warnings and cycling. *Resource and Energy Economics*, 49:165–185.

Sager, L. (2016). Estimating the effect of air pollution on road safety using atmospheric temperature inversions. *Grantham Research Institute on Climate Change and the Environment working paper*, 251.

Schultz, P. W., Nolan, J. M., Cialdini, R. B., Goldstein, N. J., and Griskevicius, V. (2007). The constructive, destructive, and reconstructive power of social norms. *Psychological science*, 18(5):429–434.

Schultz, W. P., Khazian, A. M., and Zaleski, A. C. (2008). Using normative social influence to promote conservation among hotel guests. *Social influence*, 3(1):4–23.

Sheeran, P. (2002). Intention—behavior relations: a conceptual and empirical review. *European review of social psychology*, 12(1):1–36.

Silva, A. and John, P. (2017). Social norms don't always work: An experiment to encourage more efficient fees collection for students. *PloS one*, 12(5):e0177354.

Simis, M. J., Madden, H., Cacciatore, M. A., and Yeo, S. K. (2016). The lure of rationality: Why does the deficit model persist in science communication? *Public Understanding of Science*, 25(4):400–414.

Staunton, M., Louis, W. R., Smith, J. R., Terry, D. J., and McDonald, R. I. (2014). How negative descriptive norms for healthy eating undermine the effects of positive injunctive norms. *Journal of Applied Social Psychology*, 44(4):319–330.

Steinbach, R., Green, J., Datta, J., and Edwards, P. (2011). Cycling and the city: a case study of how gendered, ethnic and class identities can shape healthy transport choices. *Social science & medicine*, 72(7):1123–1130.

Sun, C., Kahn, M. E., and Zheng, S. (2017). Self-protection investment exacerbates air pollution exposure inequality in urban china. *Ecological Economics*, 131:468–474.

Sunstein, C. R. (2007). On the divergent american reactions to terrorism and climate change. *Colum. L. Rev.*, 107:503.

Tainio, M., de Nazelle, A. J., Götschi, T., Kahlmeier, S., Rojas-Rueda, D., Nieuwenhuijsen, M. J., de Sá, T. H., Kelly, P., and Woodcock, J. (2016). Can air pollution negate the health benefits of cycling and walking? *Preventive Medicine*, 87:233–236.

TFL (2016). Attitudes towards cycling library report – september 2016 (online). http://content.tfl.gov.uk/attitudes-to-cycling-2016.pdf [Accessed: 23 January 2018].

Thøgersen, J. (2006). Norms for environmentally responsible behaviour: An extended taxonomy. *Journal of Environmental Psychology*, 26(4):247–261.

Thorndike, A. N., Riis, J., and Levy, D. E. (2016). Social norms and financial incentives to promote employees' healthy food choices: A randomized controlled trial. *Preventive medicine*, 86:12–18.

Underwood, E. (2017)). The polluted brain. http://www.sciencemag.org/news/2017/01/brain-pollution-evidence-builds-dirty-air-causes-alzheimer-s-dementia[Accessed: 23 January 2018].

Van Der Linden, S. (2015). Exploring beliefs about bottled water and intentions to reduce consumption: The dual-effect of social norm activation and persuasive information. *Environment and Behavior*, 47(5):526–550.

Vinnell, L. J., Milfont, T. L., and McClure, J. (2018). Do social norms affect support for earthquake-strengthening legislation? comparing the effects of descriptive and injunctive norms. *Environment and Behavior*, page 0013916517752435.

Ward, A. L. S. and Beatty, T. K. (2016). Who responds to air quality alerts? *Environmental and Resource Economics*, 65(2):487–511.

Weichenthal, S., Kulka, R., Dubeau, A., Martin, C., Wang, D., and Dales, R. (2011). Traffic-related air pollution and acute changes in heart rate variability and respiratory function in urban cyclists. *Environmental Health Perspectives*, 119(10):1373.

Welsch, H. (2006). Environment and happiness: Valuation of air pollution using life satisfaction data. *Ecological economics*, 58(4):801–813.

Wen, X.-J., Balluz, L., and Mokdad, A. (2009). Association between media alerts of air quality index and change of outdoor activity among adult asthma in six states, brfss, 2005. *Journal of community health*, 34(1):40–46.

WHO (2016). Who global urban ambient air pollution database. http://www.who.int/phe/health_topics/outdoorair/databases/cities/en/ [Accessed: 23 January 2018].

Yeomans, M. and Herberich, D. (2014). An experimental test of the effect of negative social norms on energy-efficient investments. *Journal of Economic Behavior & Organization*, 108:187–197.

Young, H. P. (2015). The evolution of social norms. *economics*, 7(1):359–387.

Zeidner, M. and Shechter, M. (1988). Psychological responses to air pollution: Some personality and demographic correlates. *Journal of Environmental Psychology*, 8(3):191–208.

Zhang, J. and Mu, Q. (2017). Air pollution and defensive expenditures: Evidence from particulate-filtering facemasks. *Journal of Environmental Economics and Management*. https://doi.org/10.1016/j.jeem.2017.07.006[Accessed: 23 January 2018].

Zivin, J. G. and Neidell, M. (2009). Days of haze: Environmental information disclosure and intertemporal avoidance behavior. *Journal of Environmental Economics and Management*, 58(2):119–128.

Zivin, J. G. and Neidell, M. (2013). Environment, health, and human capital. *Journal of Economic Literature*, 51(3):689–730.

Zuurbier, M., Hoek, G., Oldenwening, M., Meliefste, K., van den Hazel, P., and Brunekreef, B. (2011). Respiratory effects of commuters' exposure to air pollution in traffic. *Epidemiology*, pages 219–227.

5.8 Tables and Figures

Figure 5.1: Control and treatment group messages on air pollution health risks, avoidance and face-masks

(a) Control group: Information

THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

Air pollution is a major environmental risk to health - over 9,000 Londoners die prematurely every year, because of long-term exposure to air pollution.

London broke the annual air pollution limit just 5 days into 2017, and every borough recorded illegally high levels of toxic Nitrogen Dioxide (NO_2).

High concentrations of NO_2 and other air pollutants are linked to increased risk of respiratory and lung diseases like asthma, cardiac diseases, cancer, adverse birth outcomes and mortality.

Cyclists are exposed to dangerously high levels of pollutants, although they pollute the environment less, and could be less at risk compared to people using cars, buses and the tube.

Source: King's College, University of London and Greater London Authority.

Using an anti-pollution face-mask reduces your personal exposure to air pollution.

It filters out pollutants such as PM2.5, sub-micron particulates, unburnt fuel and traffic fumes, lowering air pollution risks and thereby improving your health.

(b) Treatment group: Information + Social norms

THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

Air pollution is a major environmental risk to health - over 9,000 Londoners die prematurely every year, because of long-term exposure to air pollution.

London broke the annual air pollution limit just 5 days into 2017, and every borough recorded illegally high levels of toxic Nitrogen Dioxide (NO_2).

High concentrations of NO_2 and other air pollutants are linked to increased risk of respiratory and lung diseases like asthma, cardiac diseases, cancer, adverse birth outcomes and mortality.

Cyclists are exposed to dangerously high levels of pollutants, although they pollute the environment less, and could be less at risk compared to people using cars, buses and the tube.

Source: King's College, University of London and Greater London Authority.

Please don't leave yourself unprotected while breathing toxic air.

An increasing number of cyclists are using anti-pollution masks to shield themselves.

Furthermore, 90% of Londoner's think air pollution is a big problem requiring urgent action.

Using an anti-pollution face-mask reduces your personal exposure to air pollution.

It filters out pollutants such as PM 2.5, sub-micron particulates and unburnt fuel to improve your health by lowering air pollution health risks.

Figure 5.2: Proportion of subjects choosing face-mask (ATE, N = 181)

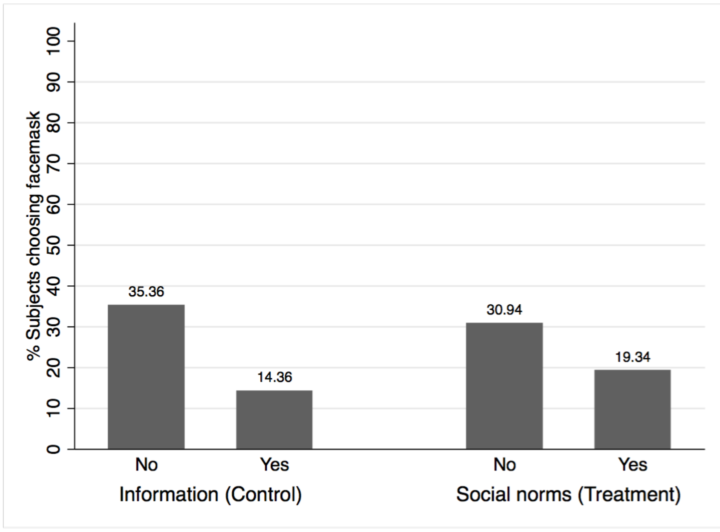


Figure 5.3: Proportion of subjects choosing face-mask (ATT, N = 164)

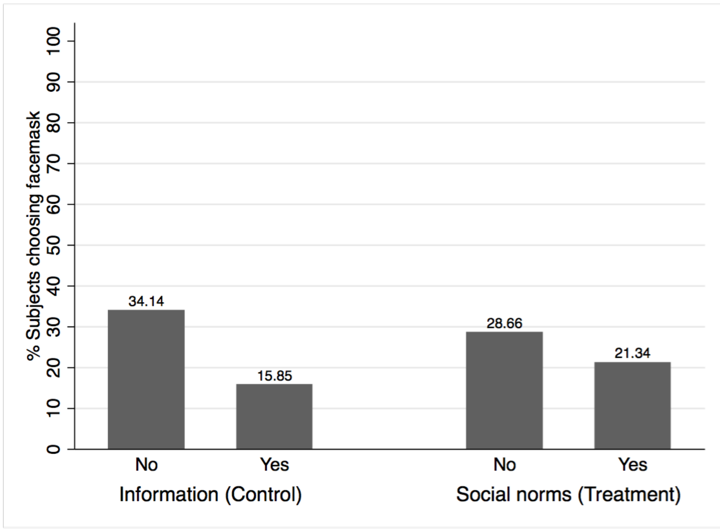


Table 5.1: Treatment effects

Treatment effect by sample	Average Treatment Effect (ATE)		Average Treatment Effect on the Treated (ATT)	
Logit models	(1)	(2)	(3)	(4)
Treat = 1, Social norms	0.431	0.411	0.472	0.468
	(0.32)	(0.33)	(0.33)	(0.33)
Constant	-0.901***	-1.131*	-0.767***	-0.937
	(0.23)	(0.60)	(0.24)	(0.62)
Observations	181	181	164	164
Survey dummies	No	Yes	No	Yes
Wald chi2(1)	1.84	6.1	2.09	5.37
Prob >chi2	0.175	0.412	0.148	0.498
Pseudo R2	0.008	0.027	0.01	0.027

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Binary outcome variable of choice of face-mask (or not). Independent variable: exposure to normative message. The logistic regression coefficients give the change in the log-odds of the outcome for a one unit increase in the predictor variable. Surveyor dummies include surveyor and location dummies.

Figure 5.4: Choice of face-mask regressed onto control versus normative message for cyclists with Low and High Perceived Air Quality in London (PAQL)

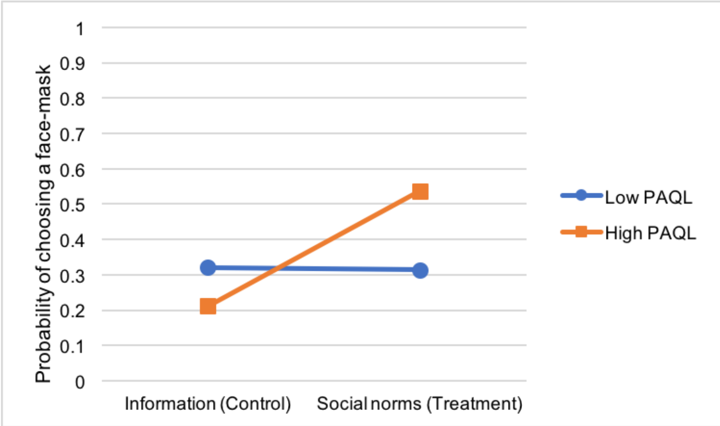


Table 5.2: Heterogeneous treatment effects: Perceived Air Quality in London (PAQL)

Treatment effect by sample	Average Treatment Effect (ATE)		Average Treatment Effect on the Treated (ATT)	
Logit models	(1)	(2)	(3)	(4)
Treat = 1, Social norms	0.067	-0.031	0.078	0.021
	(0.38)	(0.39)	(0.39)	(0.40)
High PAQL = 1, Optimistic about air quality	-0.497	-0.582	-0.519	-0.593
	(0.57)	(0.55)	(0.58)	(0.56)
Treat (=1) x High PAQL (=1)	1.288*	1.545**	1.422*	1.599**
	(0.74)	(0.74)	(0.77)	(0.76)
Constant	-0.784***	-1.032	-0.644**	-0.804
	(0.26)	(0.66)	(0.27)	(0.67)
Observations	181	181	164	164
Survey dummies	No	Yes	No	Yes
Wald chi2(1)	5.38	11.24	6.06	10.57
Prob >chi2	0.146	0.188	0.109	0.227
Pseudo R2	0.024	0.049	0.029	0.05

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Binary outcome variable of choice of face-mask (or not). Independent variable: exposure to normative message. Moderator variable: Binary variable of Perceived air quality in London (High or Low PAQL). The logistic regression coefficients give the change in the log odds of the outcome for a one unit increase in the predictor variable. Surveyor dummies include surveyor and location dummies.

Chapter 6

The effect of imperfect monitoring and punishment networks in a common pool resource dilemma

6.1 Introduction

Peer monitoring and punishment is an important means to mitigate free-riding in social dilemmas. Ostrom et al. (1992, 1994) demonstrate that individuals monitor and punish free-riders even at personal cost, in Common-Pool Resource (CPR) appropriation dilemmas. Fehr and Gachter (2000) find that cooperation is lower without peer punishment in Public Goods (PG) experiments. But many extant studies implicitly assume perfect monitoring and punishment, i.e., everyone can monitor and punish everyone else.[1]

Recent experimental evidence reveals that imperfect peer monitoring and punishment, i.e., where all agents cannot monitor and punish eveeryone in the group, represented by an underlying network that connects agents, impact cooperation in voluntary contribution mechanism (VCM) PG experiments (Carpenter et al., 2012; Leibbrandt et al., 2015; Boosey and Isaac, 2016). For instance, Carpenter et al. (2012) find the network architecture impacts contributions, punishment and welfare. Leibbrandt et al. (2015) find that contributions to the public good are higher when more punishment opportunities are available, but that punishment is also higher. Boosey and Isaac (2016) note that the network structure affects the incidence of anti-social punishment. We extend this literature, by providing new experimental evidence on how the monitoring and punishment network architecture, affects behaviour and beliefs in a CPR appropriation dilemma.

CPR appropriation dilemmas represent strategic situations, where one agent's consumption of resource units, such as fish or water, removes those units from the resource system. Unlike public goods dilemmas, an agent's appropriation inflicts a negative externality on others through the reduction in payoffs, due to the rivalry of resource units (Ostrom et al., 1994).[2] The baseline appropriation game, pioneered by Ostrom et al. (1992), uses a non-linear payoff function to locate the socially optimal and selfish equilibria in the interior of the strategy space. This non-linear payoff structure aims to approximate the complexity faced by agents in the field, arising from socio-ecological dynamics (Ibid.).

The role of peer punishment in non-linear CPR appropriation dilemmas is under-examined. Although Ostrom et al. (1992)'s seminal paper is widely cited to demonstrate the effectiveness of peer punishment, the original study reports punishment is erratic and

[1] See Anderies et al. (2011); Poteete et al. (2010) and Ostrom (2006) for a review of CPR experiments in the lab and field, and Sturm and Weimann (2006) and Noussair and van Soest (2014) for a review CPR experiments alongside other environmental dilemmas. Chaudhuri (2011) and Ledyard (1995) survey PG experiments.

[2] A PG game models a 'provision' dilemma, where others' contributions generate a positive supply externality because the good is non-excludable and non-rival (Ostrom, 2006). While under certain conditions the CPR and PG can can be strategically equivalent (e.g. see Ledyard (1995)), CPR dilemmas remain theoretically distinct because of the aspect of rivalry or the subtractability of the yield from the CPR (Apesteguia and Maier-Rigaud, 2006; Ostrom et al., 1992).

has a limited impact on cooperation (also see Ostrom et al. (1994). In a recent study, Cason and Gangadharan (2015) also observe that peer punishment has a weaker impact on appropriation, resulting in outcomes closer to the Nash equilibrium in non-linear CPR games, compared to linear VCM PG games. They note, "... the effectiveness of peer punishment could vary in different environments; particularly in situations with more complexity that makes it more difficult to identify defectors" (in Cason and Gangadharan (2015), pp. 86). Welfare is also lower, as punishment reduces payoffs.[3] More research is required to understand the impact of peer monitoring and punishment, in social dilemmas characterised by complex non-linear payoffs, and resource rivalry.

We addressed this literature gap, by exploring the role of the network architecture in promoting cooperation in a non-linear CPR appropriation dilemma, using a lab experiment. We exogenously varied the monitoring and punishment network, which in turn jointly determined feedback and punishment opportunities available to agents. Appropriation from the CPR, stated beliefs about other member's appropriation, and punishment was compared over fifteen rounds of play, in groups of four using a stranger-matching protocol.

We selected four regular types of networks with non-trivial local and global network properties: the complete, the undirected circle, the directed circle and line networks. This choice of networks yields two advantages. First, it allowed us to examine if outcomes vary as the number of monitoring and punishment opportunities available to agents systematically declines. Second, we could focus on the impact of four graph-theoretical properties of the network architecture, namely completeness, connectedness or directedness, and node degree (network properties are defined in section two). Thus, our contribution is primarily an empirical one: highlighting how beliefs and behaviour vary due to the joint effect of the monitoring and punishment network architecture.

It is not immediately evident that perfect monitoring and punishment networks necessarily increase cooperation. On the one hand, they allow agents a higher opportunity to punish more agents to mitigate over-appropriation. On the other hand, agents face a second-order monitoring dilemma, if coordinating costly punishment decisions becomes more difficult in well-connected networks. In this case, agents in imperfect, less-connected networks can focus their punishment on their immediate neighbours, and punishment may be more severe. Besides, agents may find it especially challenging to differentiate between the free-riding and socially efficient appropriation, due to the complexity of the non-linear

[3]On the other hand, recent experiments find behaviour in non-linear PG, and CPR games qualitatively similar, as cooperation starts near the socially optimal level and trends towards but remains below the selfish equilibrium (Kingsley, 2015; Kingsley and Liu, 2014; Apesteguia and Maier-Rigaud, 2006).

strategy space. Since perfect monitoring and punishment networks offer greater opportunities for information feedback, it can facilitate a greater (and faster) convergence between beliefs over other's appropriation and their actual behaviour, compared to less-connected networks.[4]

The primary finding from our study was that complete networks – the baseline with perfect monitoring and punishment – elicited the lowest payoffs to agents, and are consequently the least efficient. As average appropriation is not significantly different across networks, this result is primarily driven by heavy punishment received by subjects in the complete network. While free-riders, i.e., those who appropriate more than the Pareto appropriation level, were sanctioned in all networks, those who appropriated less than the Pareto optimal level were sanctioned less in undirected and connected networks. Completeness was significantly associated with higher punishment and beliefs, and lower efficiency. We also found that subject's beliefs underestimated other's appropriation across networks. The difference between beliefs and other's (mean) appropriation declined with time. However, this decline was contingent on the type of network: subjects in the undirected circle and directed circle networks recorded higher average differences in the last period of play (rounds 11-15), compared to the nodes in the complete network.

Our paper contributes to the experimental literature on how to mitigate the over-appropriation of common-pool resources with peer monitoring. This includes work on peer monitoring and punishment (Cason and Gangadharan, 2015; Kingsley, 2015; Janssen et al., 2010; Casari and Plott, 2003; Ostrom et al., 1992), communication with peer monitoring (Ostrom et al., 1992; Cardenas et al., 2004; Cason and Gangadharan, 2016), and the relative effectiveness of rewards over fines vyrastekova2008. Ostrom et al. (1992); Cason and Gangadharan (2015) and Kingsley (2015) are the closest to our study because they also use a non-linear CPR appropriation game with peer punishment.[5] While they examine the impact of perfect peer monitoring and punishment, we used perfect monitoring and punishment as the baseline and vary the structure of monitoring and

[4]The natural resource governance literature provides empirical support that well-connected social networks elicit both cooperation and over-appropriation. For instance, King (2000) finds that high levels of social interaction and dense social ties amongst local fisherman enabled them to manage unfavourable developments related to the local fishery. Conversely, Bodin and Crona (2008), find that despite dense social ties, fishers in another Kenyan fishing village were reluctant to call out rule-breaking and had few institutions to overcome over-exploitation of local fisheries. One of the possible reasons they outline, is the homogeneity of information and behaviour among key individuals, leading to reduced problem recognition. See Bodin and Crona (2009) for a review of this literature.

[5]Related studies on peer monitoring in CPR games includes the following. Casari and Plott (2003) experimentally test a historically-rooted peer punishment institution where punishers receive the 'fines' paid by the punished and find punishment improves cooperation. Vyrastekova and Van Soest (2008) use a quadratic CPR game and find punishment is better than rewards at eliciting cooperation. Janssen et al. (2010) incorporate complex temporal socio-ecological dynamics in the CPR game but do not find punishment to be effective in increasing cooperation.

punishment instead. Other key differences relate to the experimental design: we used a strangers-matching protocol, to minimise investment in strategic play and reputation, and to retain our focus on the network architecture.[6] We also elicited incentivised beliefs in the first stage, as discussed in the following paragraphs.

We also extend the literature on how imperfect peer monitoring and punishment impacts cooperation in linear VCM PG games (Boosey and Isaac, 2016; Leibbrandt et al., 2015; Carpenter et al., 2012).[7] A consistent finding was that incomplete but connected networks elicit at least as many contributions to the public good as complete networks (Boosey and Isaac, 2016; Leibbrandt et al., 2015; Carpenter et al., 2012). Carpenter et al. (2012) are most closely related to our experiment, as they examine the joint effect of the monitoring and punishment network architecture, using a strangers-matching design. They find that relatively lower punishment in the complete network makes it more efficient than other network structures. On the other hand, Leibbrandt et al. (2015) and Boosey and Isaac (2016) vary only the punishment network and find that subjects use greater punishment when more punishment opportunities are available, but that individual punishment behaviour depends on the type of network. Apart from using a non-linear CPR game, we differ from these studies by eliciting incentivised beliefs about the expected appropriation of others in the network.[8]

Experimental evidence on beliefs from linear CPR games (Velez et al., 2009) and linear VCM PG games (Croson, 2000; Neugebauer et al., 2009; Fischbacher and Gachter, 2010; Gächter and Renner, 2010; Smith, 2013) offers two consistent findings: first, subjects consistently state 'optimistic' beliefs by overestimating other's contributions (or underestimating appropriation), and second, beliefs are positively correlated with contributions. We extend this literature, by eliciting incentivised beliefs across all networks to empirically explore if stated beliefs and beliefs accuracy varies by network architecture.

One means of increasing beliefs accuracy (i.e., reducing the difference between stated beliefs and other's revealed behaviour) is by incentivising beliefs (Gächter and Renner, 2010). Instead, we explored if feedback about other's appropriations, which is determined

[6]We also modify the punishment technology, such that punishment points that can be allocated by subjects depend on their earnings in the first stage (following Carpenter et al. (2012); also see Nikiforakis (2008).

[7]See Kosfeld (2004) and Choi et al. (2016) for reviews of experiments on networks in the lab.

[8]Another difference is that we increase the cost of punishment, such that the cost of receiving one deduction point is three tokens. This matches a standard fee-to-fine ratio used in CPR experiments but is higher than Carpenter et al. (2012) who use a fee-to-fine ratio of 0.5:1 (i.e., it costs the punisher 0.5 tokens to assign one deduction point). Leibbrandt et al. (2015) and Boosey and Isaac (2016) also use a partners-matching protocol, to allow the formation of agent's reputations. They use a different punishment technology that endows players with additional tokens in stage two to assign punishment. Boosey and Isaac (2016) also use a 1:3 fee-to-fine ratio.

by the network architecture, impacts stated beliefs and belief accuracy. Given the complexity of the non-linear CPR game, uninformed agents may face greater difficulties in thinking of other's expected appropriations because they lack common knowledge about other's revealed behaviour in the lab. Conversely, informed agents in better-connected networks can learn more accurately about the appropriation of other agents in the network in each round.[9] Greater feedback may lead to a faster convergence between beliefs and behaviour, and therefore higher belief accuracy, in better-connected networks, with a larger share of informed agents.[10] To the best of our knowledge, we are unaware of any other studies which elicit beliefs in either a non-linear CPR dilemma or alongside the monitoring and punishment network architecture.[11]

The paper is organised as follows. Section 2 introduces the networks and the structural graph properties; this is followed by a description of the CPR appropriation dilemma and the key hypotheses. Section 3 outlines the experimental design, and section 4 presents the results. We discuss the potential implications for our results and conclude with a discussion in section 5.

6.2 Conceptual framework

6.2.1 Network architecture and properties

Figure 6.1 (Panel 1A-D), illustrates the four monitoring and punishment networks used in the experiment, and their graph-theoretic properties. A network consists of three agents or appropriators indexed by $i = A, B, C, D$. An edge between two agents indicates that they are connected, and the arrowhead points to the agent whose appropriation can be monitored and punished. For each subject i, N_i denotes the set of subjects $j \neq$i who can be monitored by i; in other words, N_i is the monitoring neighbourhood of subject i. An 'undirected' or bi-directional edge between any two nodes implies that the pair of extractors can monitor and punish each other. Conversely, a 'directed' or unidirectional edge denotes that only the extractor to whom the edge points can be observed and punished, but not vice-versa. Thus, if an edge runs from i to j, then i can monitor j ($j \in N_i$), but

[9]Notably, previous work has remarked that the greater complexity in non-linear CPR appropriation dilemmas is an important feature impacting appropriation and punishment behaviour (e.g. in Cason and Gangadharan (2015)). Others have noted subjects may experience greater confusion in the CPR appropriation game in the lab (Sturm and Weimann, 2006).

[10]Some intuition can be obtained from models of social learning on networks, although they do not directly model appropriation in CPR dilemmas. For instance, Gale and Kariv (2003) predict that subject's beliefs and behaviour, ought to converge faster in well-connected networks with more informed subjects, and this is experimentally verified in guessing game in Choi et al. (2012).

[11]As the goal of our paper is to examine if the network properties impact reported beliefs in systematic ways, it we do not systematically explore if beliefs (and beliefs elicitation) impacts appropriations.

j cannot monitor i ($i \notin N_j$).

[Figure 6.1]

We considered four key properties: completeness, directedness, connectedness, and node degree. The first three are global properties of the network architecture, while the fourth is a local property of the monitoring neighbourhoods that characterise the network. The definition of each network property is briefly summarised below.

Completeness [network 0]: each pair of nodes is connected by an undirected edge to represent perfect monitoring, i.e. everyone can observe everyone's appropriations and can choose to punish any extractor in the network. Networks [1-3] are incomplete.

Directedness [networks 1-2]: if the edge between pairs of nodes is not bidirectional, the network is a directed network [networks 2 and 3]; otherwise it is undirected [networks 0 and 1].

Connectedness [networks 1, 2 and 3]: if every pair of nodes and are connected by a path, the network is connected [networks 1-3]; otherwise it is disconnected [network 4]. A 'path' is a sequence of nodes wherein each node in the graph is used only once.

Node degree: the number of edges that end at a given node. The out-degree (in-degree) of node i is the number of edges with i as their initial (terminal) node. Specifically, the out-degree of subject i is the number of subjects j that can be monitored and punished by i ($j \in N_i$) and the in-degree of subject i is the number of subjects j that can monitor i ($i \in N_j$). Since nodes are defined by their out- and in-degrees, we can index them as Nn, in, out where n is the number of each network indicated in Figure 6.1, and in and out represent the number of in- and out-degrees respectively. For instance, the complete network consists of four identical or symmetric nodes denoted by N033, where each node has three in-degrees and three out-degrees.

The complete network (Figure 6.1, Panel 1A) represents perfect monitoring and punishment and is the baseline. It is complete, connected, and undirected, with symmetric nodes denoted by N033. The undirected circle network (Panel 1B) is incomplete, connected and undirected, also with symmetric nodes N122. The directed circle (Panel 1C) is a directed network, which is incomplete and connected with symmetric nodes, N211. Finally, the directed line network (Panel 1D) is the only disconnected network, which is incomplete and directed, with asymmetric nodes: N301 (Node A) cannot be monitored or punished (but can extend punishment to Node B); N311 (Nodes B and C) can be monitored and can punish one agent; N310 (Node D), can be monitored and punished, but cannot monitor or punish anyone.

6.2.2 The CPR appropriation dilemma

We modified the baseline CPR appropriation dilemma from Ostrom et al. (1992). In stage one, each agent was endowed with an equal initial amount of effort e. Agents simultaneously chose how to allocate this initial amount of effort between CPR appropriation and an outside-option activity that yields a constant marginal rate of return (e.g., agricultural labour at a given wage rate), w. Specifically, we denoted the appropriation effort of agent i by $x_i \in [0, e]$. Hence, the total appropriation effort of all agents within the network is $X = \sum_i x_i$.

The total return on appropriation is given by a concave function: $F(X) = aX - bX^2$. This concave function captures the dynamic wherein initial appropriation from the CPR pays an agent better than the opportunity cost of forgone safe appropriation (e.g. return from agricultural wages, where $F(0) = 0$ and $F'(0) > w$). But if the agent use all their endowment to appropriate from the CPR (and all agents do the same), then the outcome is counter-productive ($F'(ne) < 0$). Thus, as noted by Ostrom et al. (1992), the yield from the CPR reaches a *maximum net level* when individuals invest some, but not all, of their endowments in the CPR. Therefore, this function yields a non-linear payoff structure where it is initially more profitable to allocate some portion of the endowment - but not all of the endowment - to the CPR.

Since the CPR is non-excludable and rival in consumption, the return from appropriation to an individual agent is proportional to the ratio between her appropriation effort (x_i), and the total effort of all appropriators (X). The ratio x_i/X is called the individual distribution factor (Apesteguia and Maier-Rigaud, 2006) and captures the negative externality from appropriating rival resource units. The higher x_i is in relation to X, the higher is x_i's appropriation from the common pool resource, allowing an appropriator to capture a larger share of returns from the common pool resource ($aX - bX^2$). This set-up creates the social dilemma, where each agent has a dominant strategy to appropriate at the inefficient level from the CPR. The first-stage payoff of each agent is given by:

$$\Pi_i^1 = w(e - x_i) + (x_i/X)(aX - bX^2) \tag{6.1}$$

In the second stage, agents can observe the appropriation of those they are connected to by the network and punish over-appropriation at some cost. Each agent, i can punish

j ($j \in N_i$) to reduce j's payoff from the first stage by p_j^i at a personal unit cost of c_1, such that $0 < c_1 \leq 1$. Each punishment point received reduces j's payoff by some factor c_2 ($0 \leq c_2$). The payoff to each agent from stage two is the maximum between 0 and the net return from stage one;

$$\Pi_i^2 = max \left\{ 0, \Pi_i^1 - c_1 \sum_{j \in N_i} p_j^i - c_2 \sum_{i \in N_j} p_i^j \right\} \tag{6.2}$$

If we assume rational and self-interested agents, by backwards induction, it follows that punishment in stage two cannot deter free-riding in stage one, irrespective of the network architecture. Specifically, as punishment is costly, each subject will issue no punishment in stage two (p_i^j, for all i and $j \in N_i$). As subjects expect no punishment in stage two, they will extract at the socially inefficient level in stage one. However, as discussed earlier, evidence from linear VCM PG games suggest that the underlying structural properties of the network affect the provision of the public good. Thus, in the following section, we develop some hypotheses to test the impact of the network architecture for each outcome.

6.2.3 Hypotheses

First, previous results suggest that average contributions are similar in the complete, undirected and directed circle networks (Carpenter et al., 2012; Boosey and Isaac, 2016), but lower in the directed line network, which is a disconnected network (Carpenter et al., 2012). More broadly, they find network disconnectedness decreases contributions to the public good. This yields our first hypothesis:

Hypothesis 1: Average appropriation is similar across the complete, undirected circle and directed circle networks, but higher in the disconnected directed line network.

Second, Carpenter et al. (2012) report that subjects in the complete network tend to use lower punishment, resulting in higher than average net returns compared to many imperfect networks. They also find that punishment is used more heavily in directed networks. Conversely, Leibbrandt et al. (2015) also find that contributions are greater in well-connected punishment networks, but that received punishment is also higher with greater punishment opportunity, leading to similar payoffs. At the individual level, all studies find that free-riders (i.e., those who don't contribute to the public good) and those who contribute less than the average contribution of others in the group (i.e., low contributors) are punished more heavily. Thus, we also undertook this analysis for each network (for robustness). But given these competing arguments about the effect of the network, we formulate the following null hypotheses for punishment:

Hypothesis 2: Average punishment is similar across the complete, undirected circle, directed circle and directed line networks. Free-riders and high-appropriators are punished more heavily in all networks.

Third, we tested the null hypothesis that stated beliefs about the expected appropriation of others in the group, do not vary across networks. Agents in the complete network are perfectly informed about other's actual appropriations, and may, therefore, state more accurate beliefs, i.e., the difference between beliefs and other's appropriation may be lower. In particular, less time may be needed for beliefs and behaviour to converge in the complete network. Conversely, poorly informed agents in less-connected networks, lack of knowledge of other's actions, and may need a longer period of learning. The impact of each network type and property on beliefs accuracy is also an open empirical question, and thus we restricted our hypothesis to the effect of network completeness, which is the baseline with perfect monitoring and punishment. This yields our last two hypotheses:

Hypothesis 3: Average beliefs over other's appropriation is similar across the complete, undirected circle, directed circle and directed line networks.

Hypothesis 4: The average difference between beliefs and other's actual appropriation is lower in the complete network, relative to incomplete networks. Furthermore, the convergence of beliefs is also faster in complete networks.

6.3 Experimental design

The experiment was held at the London School of Economics and Political Science Behavioural Research Lab (LSE BRL) during November-December 2015. Participation was open only to students previously registered at the LSE BRL and was executed using z-Tree (Fischbacher, 2007). Each of the ten sessions consisted of 16-20 subjects, who were randomly assigned to a computer terminal at the start of each session, and given written instructions.[12]

[12] A concerted effort was made to ensure that subjects understood the instructions, incentives and payoffs, to ensure preferences and beliefs were measured as accurately as possible. Subjects also received payoffs table, with the written instructions. Instructions were first read by the subjects and then read aloud by the experimenter. After this, subjects answered five control questions, which were checked by the experimenter to ensure subjects familiarized themselves with the game, and only then did the experiment proceed. All instructions were framed in a neutral language (e.g. punishment points are referred to as 'deduction points'). Instructions and screen-shots of each stage of the experiment are given

We follow Carpenter et al. (2012) to hold one of the four network treatments (i.e., complete, undirected circle, directed circle, or directed line) constant throughout a given session. Subjects were randomly assigned to one of the node labels labelled A, B, C, and D, which was also fixed throughout the session. Each of the 15 rounds started with the computer randomly forming a network group of four, containing one of each type of node label. The network groups formed in each round were independent of the networks formed in any of the other rounds, and we emphasised that the groups of four would be randomly reshuffled in each round. We used this stranger-matching protocol to mitigate investment in reputations from strategic play.[13]

Each round consisted of two stages. In stage one, subjects simultaneously chose to 'place' tokens from their endowment to the common and private account and entered their beliefs over the appropriation of the other three subjects in the network. The endowment was 25 tokens, and the parameters were: a = 25, b = 0.025, and w = 5 (see equation (1)). The Nash equilibrium allocation was sixteen tokens, and the Pareto optimal allocation was ten tokens. The ratio of the Nash to Pareto equilibrium strategies was 1.6, and payoffs from the Nash and Pareto equilibrium allocation were 189 and 225 tokens respectively.[14]

Along with the appropriation decision, subjects also had to input their beliefs about the expected token placement of the other three group members in the common account, in stage one, in each round. Subjects were incentivised such that they were paid for the accuracy of their estimates, in addition to their earnings from the CPR experiment.[15] After subjects took their decision, everyone was shown their total payoffs from the first stage as shown in equation (1), and by the private and common accounts. This first stage was identical for all subjects in all treatments (including the earnings faced in the CPR

in the Appendices A and B.

[13]All sessions had 20 subjects, barring two sessions with 16 subjects due to participant absenteeism (one for the undirected circle and directed line respectively). For a typical session of 20 subjects (16): (a) the likelihood in round 1 that a player would meet another player once again during the remaining fourteen rounds was 56% (87.5%) (b) the likelihood that the same group of four players would meet during the remaining fourteen rounds was 2.24% (5.47%). Since the experiment was conducted anonymously, subjects were unable to recognise whether they were matched with a specific player in the past, but only recognised the node label (i.e., A, B, C or D).

[14]The experimental parameters were chosen to ensure a good spread in values between the Nash and Pareto equilibrium allocations as integer values, and to be comparable with the existing CPR literature (Appendix F, Table F.1). The ratio of the Nash to Pareto equilibrium strategies determines the size of the negative externality from the appropriation from the commons account.

[15]Participants were paid a financial incentive for stating correct beliefs, but it was small, to avoid hedging. Subjects received four experimental tokens each correct guess for each of the three other appropriators ($\simeq$ GBP 0.5), in addition to their experimental earnings from the CPR game.

game and beliefs).

In stage two, subjects obtained feedback about the appropriation decision of those to whom they are connected in the network, and could choose to assign deduction points based on their network and node position. Those subjects who were not able to observe other's appropriations due to their network position would only see their own decision (e.g., Node D in the Directed Line network). We held the fee-to-fine ratio of 0.33 constant in all networks, such that the cost of assigning deduction points is one token ($c_1 = 1$) and the cost of receiving a deduction point was three tokens ($c_2 = 3$). If subjects did not wish to reduce the earnings of anyone else, they had to enter zeros. The maximum deduction points that subjects could have assigned, was bound by the first stage payoffs. Although negative earnings were possible, this was very uncommon (this occurred in only 7 out of 2880 observations), and was given a value of zero for payment purposes. After both stages concluded, subjects were informed about their total payoffs according to the payoff function, and the cost of deduction points assigned and received, from equation (2). Subjects then proceeded to the next round of the 15 rounds of play, and this number of rounds was common knowledge, alongside the network structure and payoffs.

After the last round was played, we collected data on the subject's gender, and whether they studied economics, followed by a short questionnaire that explores the motivation behind decisions taken. Data on previous experience in experiments was obtained from the LSE BRL. One round was selected at random for payment, and all subjects were paid out for that round (i.e., payoffs from the game and accuracy of beliefs) at the end of the experiment such that 25 Experimental tokens = GBP 1. Each session usually lasted for an hour and 192 subjects who attended earned an average payment of GBP 11.5 each.

6.4 Results

We report the results in four subsections, corresponding to each outcome, i.e., appropriation, punishment, payoffs and beliefs. In each, we consider if outcomes vary across networks and nodes, and then explore if there are differences by network properties. We use random-effects regression models with robust standard errors clustered at the subject-level, instead of standard statistical tests, due to our experimental design. This allows us to control for potential session-fixed effects using session dummies and learning using round dummies. We also include individual-level controls for sex, experience in lab sessions and economics students.[16] Table 6.9 reports the summary statistics for the key

[16]Of the total sample, 59.35% was female, 16.15% studied economics, and the majority took part in 1-5 experiments (46.35%) and 26% in no experiment previously. Appendix F, Table F.2 presents attributes

outcomes by treatment for all rounds.

6.4.1 Appropriation

We first consider the complete network, the baseline in the literature. Average appropriation pooled across 15 rounds was 61.5% of the endowment, which is close to, albeit marginally higher than, previous studies with perfect monitoring and punishment: for example, 56.6% in Cason and Gangadharan (2015) and 59% in Kingsley (2015).

Figure 6.2 illustrates that the average appropriation across networks and for each round begins close to the mid-point of the choice interval in all treatments and trends towards the Nash equilibrium. Figure 6.3, which displays average appropriation by node and sub-period (rounds 1-5, 6-10 and 11-15; with 95% error bars), also echoes this trend. Notably, average appropriation in the complete network (N033) seems to fall marginally in the last period (also see N311). But the figures and summary statistics indicate differences in average appropriation across networks are limited.

[Table 6.1, and Figures 6.2 and 6.3]

Results of random-effects models, reported in Table 6.2, confirm that differences across networks are not statistically significant. In Table 6.2, model (1), the coefficients of the network dummies, suggest that appropriation is lower in all networks by around 1-2 tokens compared to the complete network, but this difference is weakly significant only for the undirected circle network (at 10%). In model (2), the coefficient on the Undirected circle becomes insignificant, when we include controls, including beliefs over other's appropriation for that round, and lagged appropriation, beliefs and punishment received (from the previous round). The coefficient of beliefs is negative, but not statistically significant, and that of lagged beliefs is positive and significant at 5%. As expected, the coefficient of lagged appropriation is positive and significant (at 1%), and that of lagged punishment received is negative and significant (at 1%), as expected. Similar results are reported in Table 6.3, when node dummies are used instead of network dummies. The coefficients on Nodes N122 (in the undirected circle) and N301 (player D, in directed line) are negative and weakly significant (Table 6.3, model (1)), but with the inclusion of the lagged variables, these effects disappear (Table 6.3, model (2)).

by treatment group, and shows that groups were balanced on these attributes. We replicate the analysis using Random-effects Tobit regressions with qualitatively similar results, which are omitted for brevity, but available on request.

[Tables 6.2 and 6.3]

Next, we examined the impact of the global network properties of completeness, directedness and connectedness. Recall that any differences in outcomes between the complete and undirected circle, yield the effect of completeness. Thus, we restricted the sample in Table F.4 (models (1) and (2), Appendix F), to the complete and undirected circle network, where the omitted category is the complete network. Controlling for session and round fixed-effects, and individual controls, we found that the dummy on the undirected circle was negative, but not significant, suggesting completeness had no effect on appropriations. Similarly, the effect of directedness was obtained by comparing differences in outcomes between the undirected and directed circle (Table F.5, models (1) and (2)). The effect of connectedness was obtained by comparing the differences between the directed circle and directed line (Table F.6, models (1) and (2)). Again, we found no effect due to both connectedness and directedness. We summarize these findings in our first result:

Result 1: Average appropriation is similar across the complete, undirected circle, directed circle and directed line networks, and does not differ by network completeness, connectedness and directedness or node degree.

Overall, these results support previous findings that average contributions are not statistically different between the complete, undirected circle and directed circle networks. On the other hand, we do not find that cooperation is lower due to directedness, as in Carpenter et al. (2012). As this study differs from previous experiments in numerous ways, a discussion of why the results may differ are somewhat speculative. For instance, we also elicit beliefs, which previous work has found to have either no effect on cooperation (Wilcox et al., 2000), a negative effect (Croson, 2000) or a positive effect (Gächter and Renner, 2010). How belief elicitation affects appropriation across networks in this setting in an open question. Another possibility for why appropriation is similar across networks, is that free-riding is more aggressive in non-linear CPR dilemmas, and punishment requires a longer to take effect (Cason and Gangadharan, 2015). We return to this point briefly in the following section.

6.4.2 Punishment

Table 6.1 shows that received (mean) punishment was the highest in the complete network (11.69 points), especially when compared to the mean punishment received in the directed circle and line networks (3.05 and 3.54 points respectively), and this is also evident from Figure 6.4. Punishment is also more erratic in the complete network, in line with the previous CPR literature (the undirected circle network also records higher and somewhat erratic punishment). Figure 6.5 also shows that nodes in the complete and undirected circle networks received more punishment on average. Notably, received punishment seems to be marginally declining in the last period (rounds 11-15) in the complete network, directed circle and directed line.

[Tables 6.2 and 6.3, and Figures 6.4, 6.5 and 6.6]

This suggests that higher punishment opportunities offered in the complete and undirected circle networks (i.e. the total number of punishment opportunities to each subject and by each round), elicits more positive punishment decisions and at higher levels. Indeed, Figure 6.6 shows subjects received zero punishment points 54.4% and 56.3% of the times in the complete and undirected circle networks respectively, compared to 85.8% and 80.95% in the undirected circle and line networks (68.1% for the pooled sample). Similarly, received punishment was over 15 points for 25% of the punishment opportunities in the complete network, versus 16.3%, 7% and 9.4% in the undirected circle, directed circle and directed line networks respectively.

Table 6.2 provides formal support that the complete network elicits higher punishment than the directed circle and line networks. The coefficients in model (3) suggest that controlling for other variables (rounds, sessions and individual controls), received punishment is on average around five to four points lower in the directed circle and line networks (significant at 1%). Table 6.3, model (3) also provides support that nodes in the directed networks receive less punishment than those in the complete network.

We also considered if punishment severity varied by network, i.e., received punishment divided by the number of punishment opportunities available to all nodes in each round within each network (i.e., 12 opportunities in complete network, 8 in undirected circle network, 4 in the directed circle and 3 in the directed line). From Table 6.2, Model (4), punishment severity was higher in the undirected circle relative to the complete network (significant at 5%). Similarly, when we considered punishment severity across nodes, the coefficients on N122 and N311 were positive and significant at 5%.

Network completeness, directedness and connectedness also impact punishment behaviour. In Table F.4, we examined the effect of completeness in models (3) and (4), to find that received punishment is lower in the undirected circle, relative to complete networks (at 5%), but punishment severity was not significantly different. Model (3) in Table F.5 reveals the effect of directedness, and shows that received punishment is lower in the directed line network relative to the undirected circle network (significant at 1%). Model (4) also shows punishment severity is marginally lower (weakly significant at 10%).

Finally, disconnectedness is associated with higher punishment, but this relationship is also not as robust: from Table F.6, model (3), the coefficient on punishment is positive and significant at 10%. The result on average punishment by network property is summarized as follows:

Result 2: The complete network elicited the highest levels of received punishment. Completeness was associated with higher punishment, and directedness with lower punishment.

Our results broadly correspond to Leibbrandt et al. (2015), that sanctioning is higher in the complete network, versus an incomplete one where only two subjects have sanctioning opportunities, but differ from Carpenter et al. (2012) who find that punishment levels are amongst the lowest in the complete network. As previously noted, appropriation is more aggressive, and free-riding takes longer to be identified and punished in non-linear settings. Given this, a more extended period of play may be necessary to realise the long-run benefit of punishment (including the subsequent fall in received punishment and appropriations; Gächter et al. (2008)). One possibility is that learning may be faster in the complete network, as it offers higher feedback and equal punishment opportunities. Indeed, we see that received punishment is marginally lower in the last period in Figure 6.6.[17] This suggests that lower punishment could be realised more quickly in the complete network, over a more rounds of play. However, we do not have sufficient data to conclude that is the case, at present.

Next, we proceeded to analyse individual level punishment behaviour, to examine if received punishment depended on whether subjects are free-riders. We measured 'free-riding' as the absolute positive difference between the subject's appropriation and the Pareto optimal appropriation of 10 tokens. Figures 6.7 and 6.8 present the frequency of punishment and average punishment points received by absolute deviation from the Pareto optimal appropriation respectively. Both figures show that free-riders who appropriated five tokens and above from the Pareto appropriation level received more punishment. Thus, as expected, free-riders are punished more frequently and severely. This punishment received by free-riders is typically called pro-social (or altruistic) punishment in the literature, as it is undertaken at a personal cost to the punisher(Fehr and Gächter, 2002). But we also see some anti-social punishment, albeit at lower levels, i.e., punishment targeting those who extract at or around the Pareto equilibrium (Herrmann et al., 2008). This is in line with numerous PG and CPR experiments which report the presence of

[17]A Pearson $\chi 2$ test shows that the difference between average punishment between period two (rounds 6-10) and period three (rounds 11-15) is weakly lower, with $\chi 2 = 44.75$, p-value = 0.083 in the complete network (the corresponding difference is not significant in the undirected circle network, $\chi 2 = 17.19$ and p-value = 0.143).

anti-social punishment, for reasons such as revenge, spite, confusion or to even discourage cooperation (Gintis, 2008; Nikiforakis, 2008; Casari and Plott, 2003; Ostrom et al., 1994).

[Figures 6.7 and 6.8]

We formally explore whether the patterns of punishment differs across networks. For each network, we estimated the following panel regression with individual random effects:

$$punrec_{it} = \beta_0 + \beta_1 posdev_{it} + \beta_2 negdev_{it} + \beta_3 round + \beta_4 X + \beta_5 session + \beta_6 node + u_i + e_{it} \tag{6.3}$$

We controlled for session and round dummies, node label and individual controls, and also included stage one payoffs as an additional control, because the level of received punishment was bounded by earnings from stage one (the results are robust to omitting this variable as well). The variables $posdev_{it}$ and $negdev_{it}$ refer to positive and negative deviations from the Pareto appropriation level. As a robustness check, we also examined if the (positive or negative) deviation from the (mean) appropriation of those in the network to whom the agent is directly connected to - and can be punished by - influences the level of punishment received. Note that this figure can be different for each network depending on the network and node. To illustrate, agents in complete network with perfect monitoring and punishment will be aware of the average appropriation of the other three members in the network.[18] But agents in Undirected Circle will only be aware of those agents whom they can monitor and punish, e.g. A is monitored and punished by B and D, who both can see C and A - apart from their own behaviour - since the network is connected but incomplete. Thus the absolute deviation between A and the mean appropriation of B, C and D (and so on for each subject in each round in the undirected circle). Similarly, agent A in directed line can be punished only by D, who can observe no one else because the network is directed. Thus, the absolute deviation between D (A's only punisher and neighbour) and A's appropriation is estimated, and so on. Table 6.4 presents the determinants of received punishment at the individual level in each network.

[Table 6.4]

First, we consider the complete network. Model (1) demonstrated that free-riding, measured by positive deviations from the Pareto allocation receive higher punishment (significant at 1%). The coefficient on negative deviations from the Pareto appropriation

[18] This is similar to the absolute deviation from the average appropriation of the others in the group used in Fehr and Gachter (2000) and Cason and Gangadharan (2015).

was positive but not statistically significant. However, from Model (2), we see that both positive and negative deviations from other's (mean) appropriation receives higher punishment (both coefficients significant at 1%). This highlights that both those who extract more than and less than the group norm (i.e., the mean appropriation of the other members) receives more punishment.

Models (3) and (4) also confirmed the robust presence of pro-social punishment in the undirected circle (in fact, both coefficients on the positive deviation from the Pareto and positive deviation from neighbour-punisher's appropriation are both marginally higher). But unlike the complete network, negative deviations from the Pareto, received lower punishment (significant at 5%). Along these lines, the coefficient on negative deviations from neighbour-punisher's appropriation is positive but not statistically significant. For the directed circle in Model (5), deviations above and below the Pareto optimal allocation receive higher and lower punishment respectively (significant at 1%, and 5% respectively). However, from Model (6), the coefficient on both the positive and the negative deviations from neighbour-punisher's appropriation was positive but not statistically significant. In the directed line, we also see that pro-social punishment for positive deviations from the Pareto is positive and significant (at 1%). But the coefficient on negative deviations from the Pareto is negative but not significantly different. In this case, negative deviations from other's appropriation was positive and significant at 5% (model (8); we also controlled for the node degree).

More broadly, the analysis so far suggests that different networks elicit specific patterns of punishment behaviour, apart from increasing the overall punishment capacity available to agents. While, pro-social punishment (punishment directed at subject's appropriation above the Pareto optimal) is a robust feature across networks, we found that the undirected and directed circles networks elicited systematically lower punishment for those who deviate below the Pareto appropriation level.[19] These findings are summarized in our third result:

Result 3: High appropriators and free-riders, i.e., those who appropriation above the Pareto appropriation level, were punished in all networks. Those who extracted less than the Pareto efficient allocation in incomplete and connected networks, i.e., the undirected

[19] This result is robust to the pooled panel specification with network treatment dummies and with variables positive / negative deviations from Pareto and immediate neighbour-punisher (random effects with the session / round / individual control dummies specified previously). Similar results also hold for the probability of receiving punishment, through panel probit regression models (in Table F.11). Both the marginal effects of positive and negative deviations from the Pareto level (and appropriation of Neighbour-Punishers) on both $E[punrec_{it}]$ and $Pr[punrec_{it} > 0]$ are computed and presented in Figures F.1 to F.4. Since the sign and significance levels of all the coefficients translate to each of the marginal effect, we do not report them here.

and directed circles, received lower punishment.

6.4.3 Payoffs and efficiency

Next, we compared the level of efficiency (average payoffs) across networks. Figures 9 and 10 plot the average payoffs from stage two across networks and nodes, and we see that average payoffs start above the Nash equilibrium level, but trends downwards. Table 6.1 also shows that average payoffs are the lowest in the complete network. This finding is formally supported by the random-effects regressions in Table 6.2, Model (5), which show that earnings are 17-19 tokens lower in incomplete networks (significant at 1%), controlling for session dummies, round dummies and individual controls. This is also confirmed by regression results across different nodes (Table 6.3, model (5)). We found that completeness is associated with lower payoffs (significant at 1%), but that payoffs are not different due to directedness or connectedness (Tables F.5 and F.6). As previously discussed, this result is driven by high levels of costly punishment, and rather limited differences in appropriation across networks. To summarise:

Result 4: The complete network was the least efficient network architecture, and completeness was associated with lower average payoffs.

[Figures 6.9 and 6.10]

6.4.4 Beliefs over other's appropriations

We start with discussing if beliefs over other's (mean) appropriation from the common account, vary across networks and by network property. Figures 11 and 12 disclose that stated beliefs over other's appropriation start at the Pareto appropriation and trends towards the Nash equilibrium, across networks and nodes. From Table 1, average beliefs tend to be marginally higher in complete networks compared to the undirected circle and directed circle networks.

[Figures 6.11 and 6.12]

Table 6.2, model (6) provides formal support for this when we regress the network dummies on stated beliefs, controlling for session and round dummies, and individual controls. More precisely, stated beliefs is around 2-3 tokens lower in all incomplete networks relative to the complete network (significant at 1%). This finding corresponds with Neugebauer et al. (2009), where subjects report lower beliefs with greater information feedback.[20] In model (7) we add lagged beliefs and other's appropriation in the previous period (following Fischbacher and Gachter (2010)). The coefficient on lagged beliefs is positively and significantly associated with beliefs (at 1%), but that of other's appropriation is positive, but the difference is not statistically significant. The coefficients on the network dummies fall but remain significant. These results are also qualitatively similar to those in models (6) and (7) in Table 6.3, which assess the impact of node dummies.[21] Notably, node N301, who receives no feedback on other's appropriation stated the lowest beliefs relative to nodes in the complete network; by a magnitude of around 1.6 tokens (significant at 1%; also see Figure 6.12). From Tables F.5 and F.6, directedness is negatively associated with higher beliefs, but the difference is not significant, and disconnectedness is associated with lower beliefs (significant at 5%, by around one token). This yields the following result:

Result 5: Stated beliefs over other's appropriations are the highest in the complete network. Completeness and disconnectedness are associated with higher beliefs. Node N301 states lower beliefs.

Next, we consider the deviation between stated beliefs and other's actual appropriation in more detail. Figures 13 and 14 plot the average deviation between beliefs and other's appropriation, by treatment and node, over time. There is a persistent gap between beliefs and other's mean appropriations, suggesting subjects hold 'optimistic' beliefs. The absolute difference is two tokens on average for the pooled sample. Keeping in mind differences between the current experiment and previous studies, the difference is higher than observed in Velez et al. (2009) who record that individuals expected other members would extract a nearly one unit less than their actual appropriation (non-incentivised total appropriation from others is elicited in a linear CPR game). It is relatively closer to Gächter et al. (2008) who record that the absolute difference between stated belief and actual average contribution of others is around two tokens (incentivised average contributions of other is elicited in a linear VCM PG game).

Figures 13 and 14 also reveal some differences across nodes and networks. Firstly, the absolute difference between beliefs and other's appropriation systematically falls with time in the complete network and directed line networks. On the other hand, beliefs in the undirected circle and directed circle networks seem to marginally increase in rounds

[20]Note that Neugebauer et al. (2009) provide subjects feedback about payoffs from the linear VCM PG game, broken up to the sum of partners' contributions, and from the guessing task, after each period. In addition, citetcox2015 review the literature on linear VCM PG games, and observe that the effect on feedback on other's contributions on cooperation is mixed.

[21]Notably, economics students state higher beliefs (by a magnitude of 1-0.66, significant at 1%) relative to non-economics students in Tables 6.3 and 6.4.

6-10, and then fall. Lastly, if we consider only node N301 who receives no feedback, the divergence is the highest in the first period, but drops over time.

[Figures 6.13 and 6.14, and Table 6.5]

We examine if differences across nodes are statistically significant by using random-effects models, controlling for sessions fixed-effects and individual controls.[22] We add period dummies, where period one (rounds 1-5) is the omitted category. The results are reported in Table 6.5. Model (1) shows that N301 reports the higher divergence between stated beliefs and appropriation, relative to nodes in the complete network (N033 is the omitted category). The period dummy for rounds 11-15 is negative and significant at 5%, suggesting that controlling for other variables, the deviation declines over time (or equally, belief accuracy increases with time).

To examine if this decline is contingent on the node degree, we interact the node degree dummies with the three-period dummy in model (2). First, the value of the coefficients on N301 and dummy for rounds 11-15, marginally increases and is significant at 1% each. Second, the interaction term between nodes in the undirected circle and directed circle networks (N122 and N311), and the second category of the period dummy (rounds 11-15) have a positive and significant coefficient (at 5%). This reveals that the nodes in the undirected circle and directed circle networks maintain relatively more optimistic beliefs in the last period, i.e., the difference between beliefs and other's appropriation is higher compared to nodes in the complete network in the first period (rounds 1-5), controlling for other variables. This suggests that nodes in incomplete but connected networks, maintain optimistic beliefs for longer, relative to nodes in the complete network.[23] More broadly, this confirms that the network structure impacts learning through time, and yields our last result:

Result 6: The difference between beliefs and other's actual appropriation is highest for node N301. While the deviation between beliefs and other's (mean) appropriation falls over time, trends vary by the network. Relative to the complete network, the deviation between beliefs and other's (mean) appropriation is higher in the directed circle and

[22]We focus on differences across nodes rather than networks in the text given the unique position of N301. Analogous results examining effects across networks are available in Table F.12. The results are qualitatively similar: we find that the coefficients on the undirected circle, and directed circle and line networks are not significant, but the second-period dummy for rounds 11-15 is significant. The interaction terms on the period and undirected and directed network dummies are qualitatively similar.

[23]On the other hand, Neugebauer et al. (2009) do not find that difference between beliefs and other's contributions declines over ten rounds, in groups with and without feedback. Instead, we use fifteen rounds to allow subjects greater time to learn the game and modify their behaviour, and find that average differences are more apparent in the last periods during rounds 11-15.

directed circle networks, in the last period.

6.5 Conclusion

This study contributes to the literature on peer monitoring and punishment in social dilemmas, by considering how the network architecture impacts outcomes in a non-linear CPR appropriation game. Broadly, we find evidence that the structure of the network, impacts efficiency, punishment, and stated beliefs over other's appropriation, but that it does not impact appropriation significantly.

Our results suggest the network structure impacts both punishment opportunity and the type of punishment used. While there was pro-social punishment to sanction free-riders (i.e., those who appropriate above the pareto appropriation level) in all networks, there was significantly lower punishment received by those who appropriated less than the Pareto appropriation level in the undirected and directed circle networks. The high levels of punishment in the complete network, making it the most inefficient network. Furthermore, we find that there is faster convergence between stated beliefs and other's appropriation in the complete network, relative to incomplete, but connected networks.

Overall, these findings may hold some potential lesson for policy, keeping in mind the many differences between the field and lab setting. Firstly, it highlights that the structural variation in the distribution of monitoring and punishment opportunities impacts welfare. In fact, the excessive use of punishment in the complete network provides a cautionary lesson about the cost of exclusively relying on perfect peer monitoring and punishment to enhance cooperation, especially if the primary policy objective is welfare maximisation. Second, it highlights the limited impact of the network on appropriation – suggesting the need for investigation into complementary mechanisms to enhance the effectiveness of peer monitoring, to prevent the destruction of the commons. Some of these may be especially relevant from the network perspective: for instance, the effect of restricting communication opportunities or allowing subjects to ostracise high appropriators, by severing network edges. Third, it is possible that long-run benefits of punishment maybe realised in systematically different ways across network architectures, as they all offer different opportunities for learning and feedback. Some natural extensions to this research are therefore examining how behaviour evolves over a larger number of rounds, allowing for variations in the experimental design to allow for partner-matching and different types of punishment technologies, and the systematic examination of how beliefs evolve and impact behaviour in more complex, non-linear social dilemmas.

Bibliography

Anderies, J. M., Janssen, M. A., Bousquet, F., Cardenas, J.-C., Castillo, D., Lopez, M.-C., Tobias, R., Vollan, B., and Wutich, A. (2011). The challenge of understanding decisions in experimental studies of common pool resource governance. *Ecological Economics*, 70(9):1571–1579.

Apesteguia, J. and Maier-Rigaud, F. P. (2006). The role of rivalry: public goods versus common-pool resources. *Journal of Conflict Resolution*, 50(5):646–663.

Bodin, Ö. and Crona, B. I. (2008). Management of natural resources at the community level: exploring the role of social capital and leadership in a rural fishing community. *World development*, 36(12):2763–2779.

Bodin, Ö. and Crona, B. I. (2009). The role of social networks in natural resource governance: What relational patterns make a difference? *Global environmental change*, 19(3):366–374.

Boosey, L. and Isaac, R. M. (2016). Asymmetric network monitoring and punishment in public goods experiments. *Journal of Economic Behavior & Organization*, 132:26–41.

Cardenas, J.-C., Ahn, T., and Ostrom, E. (2004). Communication and co-operation in a common-pool resource dilemma: A field experiment. In *Advances in Understanding Strategic Behaviour*, pages 258–286. Springer.

Carpenter, J., Kariv, S., and Schotter, A. (2012). Network architecture, cooperation and punishment in public good experiments. *Review of Economic Design*, 16(2-3):93–118.

Casari, M. and Plott, C. R. (2003). Decentralized management of common property resources: experiments with a centuries-old institution. *Journal of Economic Behavior & Organization*, 51(2):217–247.

Cason, T. N. and Gangadharan, L. (2015). Promoting cooperation in nonlinear social dilemmas through peer punishment. *Experimental Economics*, 18(1):66–88.

Cason, T. N. and Gangadharan, L. (2016). Swords without covenants do not lead to self-governance. *Journal of Theoretical Politics*, 28(1):44–73.

Chaudhuri, A. (2011). Sustaining cooperation in laboratory public goods experiments: a selective survey of the literature. *Experimental Economics*, 14(1):47–83.

Choi, S., Gale, D., and Kariv, S. (2012). Social learning in networks: a quantal response equilibrium analysis of experimental data. *Review of Economic Design*, 16(2-3):135–157.

Choi, S., Kariv, S., and Gallo, E. (2016). Networks in the laboratory. In *The Oxford Handbook of the Economics of Networks*. Oxford University Press.

Croson, R. T. (2000). Thinking like a game theorist: factors affecting the frequency of equilibrium play. *Journal of Economic Behavior & Organization*, 41(3):299–314.

Fehr, E. and Gachter, S. (2000). Cooperation and punishment in public goods experiments. *American Economic Review*, 90(4):980–994.

Fehr, E. and Gächter, S. (2002). Altruistic punishment in humans. *Nature*, 415(6868):137.

Fischbacher, U. (2007). z-tree: Zurich toolbox for ready-made economic experiments. *Experimental economics*, 10(2):171–178.

Fischbacher, U. and Gachter, S. (2010). Social preferences, beliefs, and the dynamics of free riding in public goods experiments. *American economic review*, 100(1):541–56.

Gächter, S. and Renner, E. (2010). The effects of (incentivized) belief elicitation in public goods experiments. *Experimental Economics*, 13(3):364–377.

Gächter, S., Renner, E., and Sefton, M. (2008). The long-run benefits of punishment. *Science*, 322(5907):1510–1510.

Gale, D. and Kariv, S. (2003). Bayesian learning in social networks. *Games and Economic Behavior*, 45(2):329–346.

Gintis, H. (2008). Punishment and cooperation. *Science*, 319(5868):1345–1346.

Herrmann, B., Thöni, C., and Gächter, S. (2008). Antisocial punishment across societies. *Science*, 319(5868):1362–1367.

Janssen, M. A., Holahan, R., Lee, A., and Ostrom, E. (2010). Lab experiments for the study of social-ecological systems. *Science*, 328(5978):613–617.

King, A. (2000). *Managing without institutions: The role of communication networks in governing resource access and control*. PhD thesis, University of Warwick Coventry.

Kingsley, D. C. (2015). Peer punishment across payoff equivalent public good and common pool resource experiments. *Journal of the Economic Science Association*, 1(2):197–204.

Kingsley, D. C. and Liu, B. (2014). Cooperation across payoff equivalent public good and common pool resource experiments. *Journal of Behavioral and Experimental Economics*, 51:79–84.

Kosfeld, M. (2004). Economic networks in the laboratory: A survey. *Review of Network Economics*, 3(1).

Ledyard, J. (1995). Public goods: A survey of experimental research. In Kagel, J. and Roth, A., editors, *The Handbook of Experimental Economics*. Princeton University Press, Princeton, NJ.

Leibbrandt, A., Ramalingam, A., Sääksvuori, L., and Walker, J. M. (2015). Incomplete punishment networks in public goods games: experimental evidence. *Experimental Economics*, 18(1):15–37.

Neugebauer, T., Perote, J., Schmidt, U., and Loos, M. (2009). Selfish-biased conditional cooperation: On the decline of contributions in repeated public goods experiments. *Journal of Economic Psychology*, 30(1):52–60.

Nikiforakis, N. (2008). Punishment and counter-punishment in public good games: Can we really govern ourselves? *Journal of Public Economics*, 92(1-2):91–112.

Noussair, C. N. and van Soest, D. P. (2014). Economic experiments and environmental policy. *Annual Review of Resource Economics*, 6(1):319–337.

Ostrom, E. (2006). The value-added of laboratory experiments for the study of institutions and common-pool resources. *Journal of Economic Behavior & Organization*, 61(2):149–163.

Ostrom, E., Gardner, R., and Walker, J. (1994). *Rules, games, and common-pool resources*. University of Michigan Press.

Ostrom, E., Walker, J., and Gardner, R. (1992). Covenants with and without a sword: Self-governance is possible. *American Political Science Review*, 86(2):404–417.

Poteete, A. R., Janssen, M. A., and Ostrom, E. (2010). *Working together: collective action, the commons, and multiple methods in practice*. Princeton University Press.

Smith, A. (2013). Estimating the causal effect of beliefs on contributions in repeated public good games. *Experimental Economics*, 16(3):414–425.

Sturm, B. and Weimann, J. (2006). Experiments in environmental economics and some close relatives. *Journal of Economic Surveys*, 20(3):419–457.

Velez, M. A., Stranlund, J. K., and Murphy, J. J. (2009). What motivates common pool resource users? experimental evidence from the field. *Journal of Economic Behavior & Organization*, 70(3):485–497.

Vyrastekova, J. and Van Soest, D. (2008). On the (in) effectiveness of rewards in sustaining cooperation. *Experimental Economics*, 11(1):53–65.

Wilcox, N. T., Feltovich, N., et al. (2000). Thinking like a game theorist: Comment. *University of Houston Department of Economics working paper*. http://www.uh.edu/~nfelt/papers/belief.pdf. [Accessed: 15 December 2017].

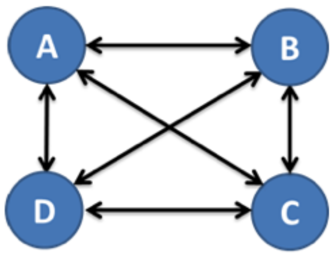
6.6 Tables and Figures

Table 6.1: Descriptive statistics by network and node

Network/Node	Sessions	Subjects	Groups	Observations	Appropriation	Punishment	Beliefs	Payoffs
Complete	3	60	225	900	15.37	11.69	13.25	172.36
					(5.56)	(23.78)	(4.84)	(51.51)
Undirected circle	2	36	135	540	14.51	6.77	12.69	188.77
					(4.99)	(14.30)	(3.75)	(37.21)
Directed circle	2	40	150	600	14.8	2.61	12.26	189.26
					(5.29)	(11.04)	(3.85)	(40.34)
Directed line	3	56	210	840	14.81	3.05	12.95	188.71
					(6.23)	(8.99)	(5.25)	(48.87)
N311	3	28	210	420	15.01	3.54	13.25	187.94
					(6.19)	(9.92)	(5.05)	(48.71)
N301	3	14	210	210	14.37	-	13.37	190.39
					(5.92)	-	(5.36)	(49.52)
N310	3	14	210	210	14.83	2.09	11.92	188.57
					(6.61)	(6.68)	(5.43)	(48.73)
Total	10	192	720	2880	14.93	6.61	12.85	183.73
					(5.62)	(17.13)	(4.61)	(46.70)

Notes: Mean (standard deviation) is reported for appropriation, received punishment, beliefs and payoffs. Subjects are assigned to one network and to a fixed node type of A, B, C or D, in each session (having 16-20 subjects), and in each of the 15 rounds, they are randomly assigned to a new group.

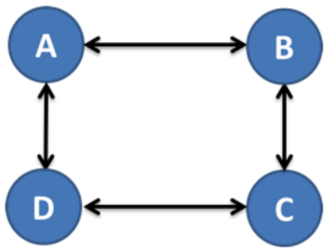
Figure 6.1: Network treatments and properties



Panel 1A: Complete network [0] (Baseline)

Global Properties:
Complete, Connected, Undirected

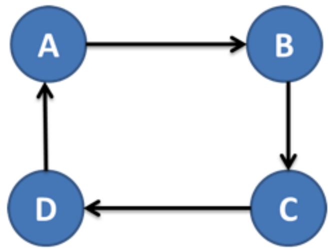
Node types: Symmetric,
A, B, C, D: N033



Panel 1B: Undirected circle network [1]

Global properties:
Incomplete, Connected, Undirected

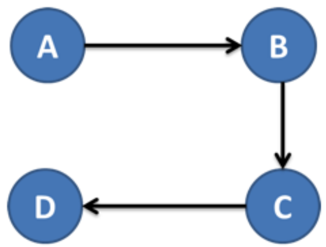
Node types: Symmetric,
A, B, C, D: N122



Panel 1C: Directed circle network [2]

Global network properties:
Incomplete Connected, Directed

Node types: Symmetric,
A, B, C, D: N211



Panel 1D: Directed line network [3]

Global network properties:
Incomplete Disconnected, Directed

Node types: Asymmetric,
A: N301
B, C: N311
D: N310

Figure 6.2: Appropriation by network

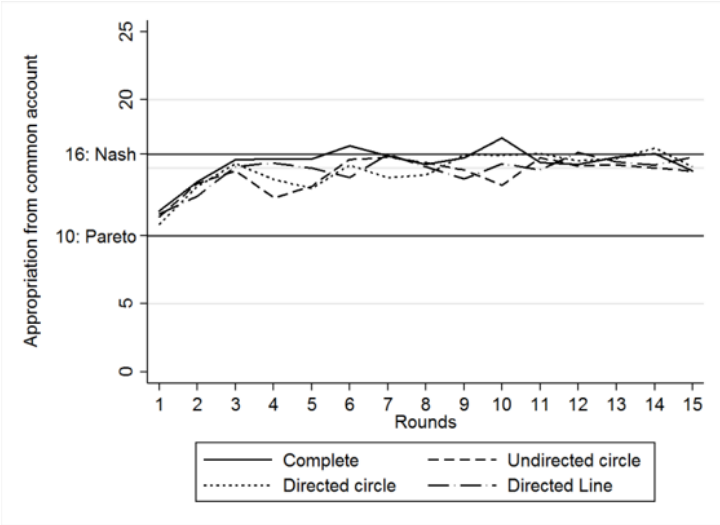


Figure 6.3: Appropriation by node

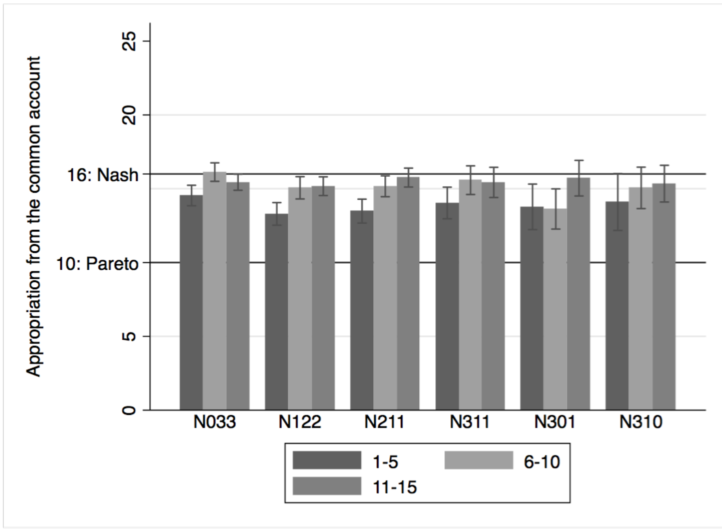


Table 6.2: Outcomes across networks

Outcome:	Appropriation	Appropriation	Received punishment	Punishment severity	Payoffs	Beliefs	Beliefs
Random-effects models:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Network = 1, Undirected circle	-2.112*	-0.937	1.892	2.277**	17.377***	-1.809**	-0.949***
	(1.20)	(0.64)	(2.33)	(1.03)	(6.15)	(0.71)	(0.35)
Network = 2, Directed circle	-1.251	-0.342	-5.229***	0.178	17.014***	-2.740***	-1.338***
	(1.14)	(0.61)	(1.86)	(1.18)	(5.85)	(0.81)	(0.40)
Network = 3, Directed line	-2.059	-0.987	-3.761**	1.405	19.711***	-3.327***	-1.814***
	(1.43)	(0.82)	(1.66)	(0.86)	(6.81)	(0.95)	(0.48)
Beliefs		-0.015					
		(0.04)					
Appropriation (t-1)		0.454***					
		-0.039					
Beliefs (t-1)		0.075**					0.528***
		(0.04)					(0.03)
Received punishment (t-1)		-0.019***					
		(0.01)					
Other's (mean) appropriation (t-1)							0.028
							(0.02)
Sex	-1.042**	-0.520*	0.874	0.59	-0.695	-0.408	-0.249
	(0.52)	(0.29)	(0.72)	(0.37)	(2.26)	(0.40)	(0.21)
Experience	-0.278	-0.063	-0.236	-0.108	-0.765	-0.405	-0.215*
	(0.30)	(0.17)	(0.45)	(0.26)	(1.50)	(0.27)	(0.13)
Economics	0.191	-0.099	-1.459**	-0.591	6.071**	1.403***	0.661***
	(0.65)	(0.34)	(0.69)	(0.40)	(2.72)	(0.42)	(0.21)
Constant	13.440***	8.743***	6.114***	1.874**	196.595***	11.780***	6.671***
	(1.24)	(0.94)	(1.89)	(0.87)	(7.33)	(0.83)	(0.69)
Observations	2,880	2,492	2,670	2,670	2,880	2,880	2,513
Number of subject	192	178	178	178	192	192	192
Session dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Round dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors are clustered at the subject level, and *** p<0.01, ** p<0.05, * p<0.1. The Complete network is the omitted category.

Table 6.3: Outcomes across nodes

Outcome:	Appropriation	Appropriation	Received punishment	Punishment severity	Payoffs	Beliefs	Beliefs
Random-effects models:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Node degree = 1, N122	-2.124*	-0.952	1.863	2.247**	17.375***	-1.847***	-0.970***
	(1.20)	(0.64)	(2.32)	(1.03)	(6.15)	(0.71)	(0.36)
Node degree = 2, N211	-1.239	-0.344	-5.213***	0.194	16.986***	-2.729***	-1.343***
	(1.14)	(0.61)	(1.86)	(1.18)	(5.86)	(0.81)	(0.40)
Node degree = 3, N311	-1.688	-0.852	-3.344**	1.841**	18.936**	-2.970***	-1.691***
	(1.61)	(0.87)	(1.65)	(0.84)	(7.52)	(1.10)	(0.54)
Node degree = 5, N310	-2.359	-1.292	-4.605***	0.524	19.380**	-4.548***	-2.310***
	(1.79)	(0.93)	(1.69)	(0.92)	(7.66)	(1.07)	(0.64)
Node degree = 4, N301	-2.503*				21.553***	-2.866***	-1.627***
	(1.49)				(7.00)	(0.95)	(0.45)
Beliefs		-0.016					
		(0.04)					
Appropriation (t-1)		0.454***					
		(0.04)					
Beliefs (t-1)		0.074*					0.525***
		(0.04)					(0.03)
Received punishment (t-1)		-0.019***					
		(0.01)					
Other's (mean) appropriation (t-1)							0.028
							(0.02)
Sex	-1.110**	-0.563*	0.753	0.464	-0.62	-0.538	-0.302
	(0.54)	(0.30)	(0.75)	(0.38)	(2.31)	(0.39)	(0.21)
Experience	-0.279	-0.069	-0.249	-0.122	-0.787	-0.429	-0.226*
	(0.30)	(0.17)	(0.45)	(0.25)	(1.51)	(0.27)	(0.13)
Economics	0.159	-0.112	-1.507**	-0.642	6.122**	1.357***	0.647***
	(0.66)	(0.35)	(0.70)	(0.40)	(2.75)	(0.43)	(0.21)
Constant	13.488***	8.815***	6.219***	1.984**	196.577***	11.908***	6.763***
	(1.24)	(0.95)	(1.89)	(0.87)	(7.34)	(0.82)	(0.70)
Observations	2,880	2,492	2,670	2,670	2,880	2,880	2,513
Number of subject	192	178	178	178	192	192	192
Session dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Round dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors are clustered at the subject level, and *** p<0.01, ** p<0.05, * p<0.1. The Complete network is the omitted category.

Figure 6.4: Received punishment by network

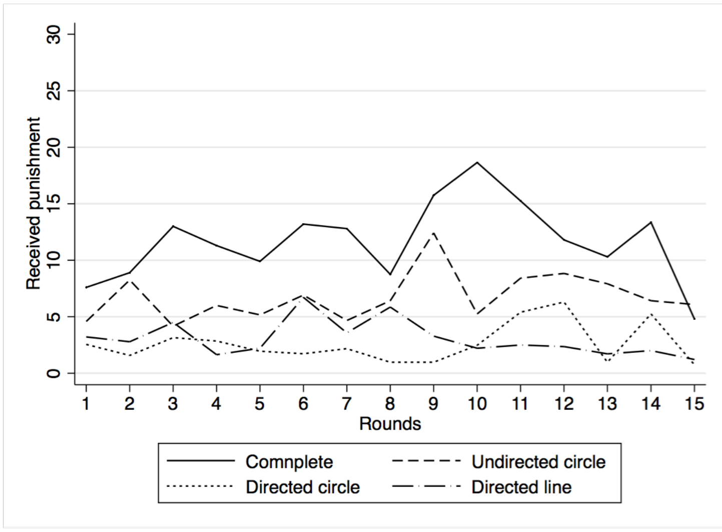


Figure 6.5: Received punishment by node

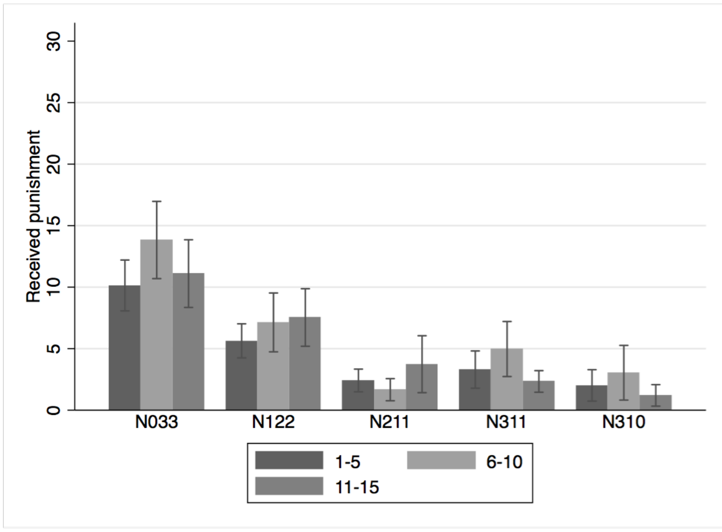


Figure 6.6: Received punishment as share of punishment opportunities

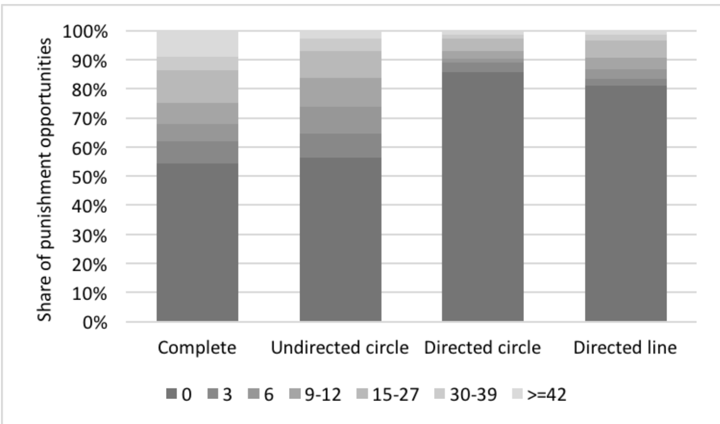


Figure 6.7: Frequency of punishment received by deviation from Pareto equilibrium and network

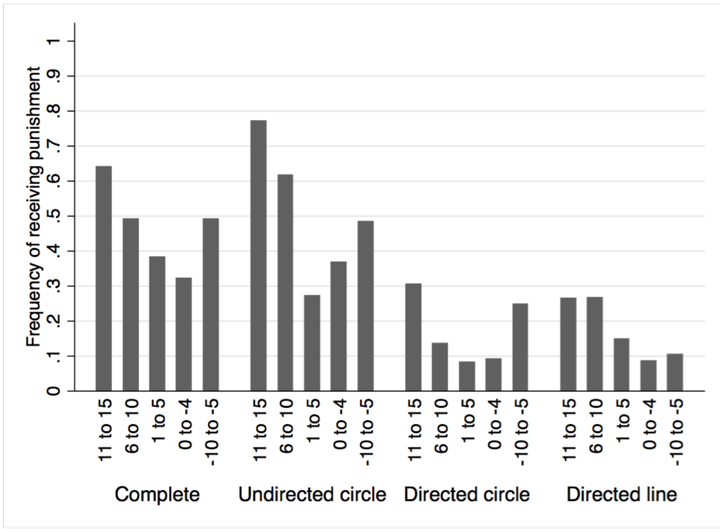


Figure 6.8: Received punishment by deviation from Pareto equilibrium and network

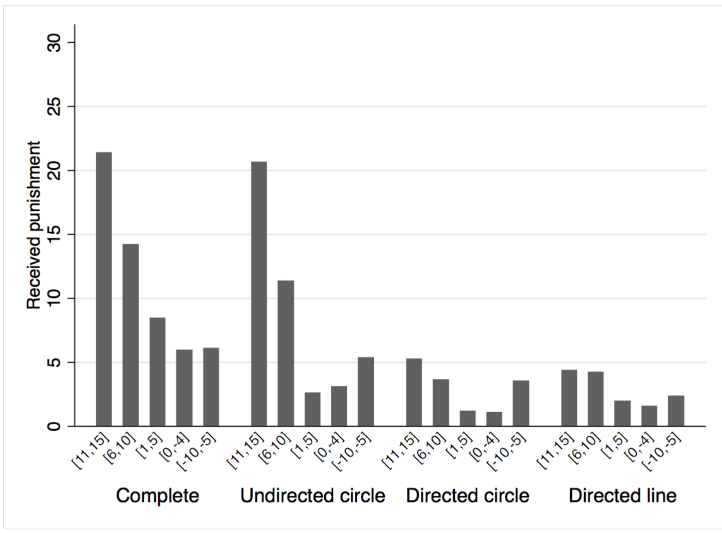


Table 6.4: Received punishment across networks

Networks:	Complete		Undirected circle		Directed circle		Directed line	
Random effects models:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Positive deviation-Pareto	1.287***		1.519***		0.378***		0.351***	
	(0.192)		(0.328)		(0.103)		(0.080)	
Negative deviation-Pareto	-0.021		-0.656**		-0.449**		-0.047	
	(0.313)		(0.314)		(0.192)		(0.171)	
Positive deviation-Neighbour/Punisher's appropriation		1.435***		2.182***		0.175		0.141
		(0.256)		(0.688)		(0.112)		(0.108)
Negative deviation-Neighbour/Punisher's appropriation		0.809***		0.317		0.143		0.213**
		(0.223)		(0.211)		(0.098)		(0.088)
Stage 1 payoff	-0.035	-0.125***	0.007	-0.048	0.021	0.004	-0.012	-0.021
	(0.023)	(0.031)	(0.022)	(0.032)	(0.021)	(0.017)	(0.013)	(0.013)
Node degree = N301, Yes							-1.242	-1.505*
							(0.786)	(0.905)
Constant	4.990	26.221***	3.313	18.264**	-6.760	-1.362	3.162	7.338**
	(5.453)	(7.143)	(5.848)	(7.411)	(6.340)	(5.285)	(3.246)	(3.518)
Observations	900	900	540	540	600	600	630	630
Number of subject	60	60	36	36	40	40	42	42
Session dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Node label	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Round dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors are clustered at the subject level, and *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The Complete network is the omitted category. Outcome variable: Received punishment; Omitted category in models (9) and (10) is Node N311.

Figure 6.9: Payoffs by network

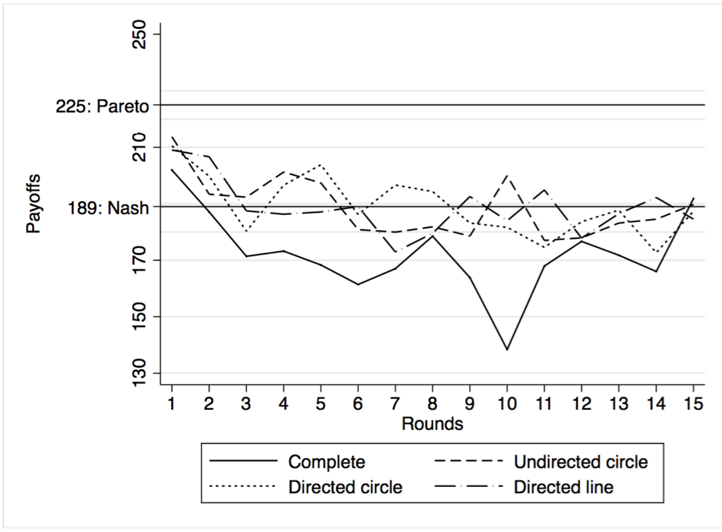


Figure 6.10: Payoffs by node

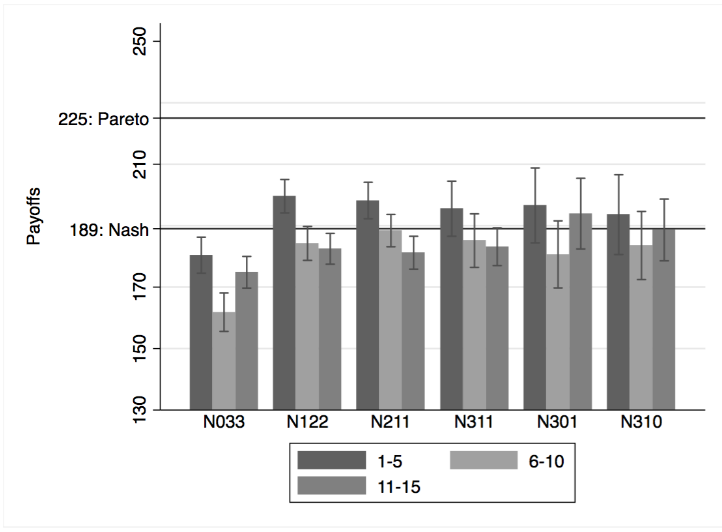


Figure 6.11: Belief's over other's appropriation by network

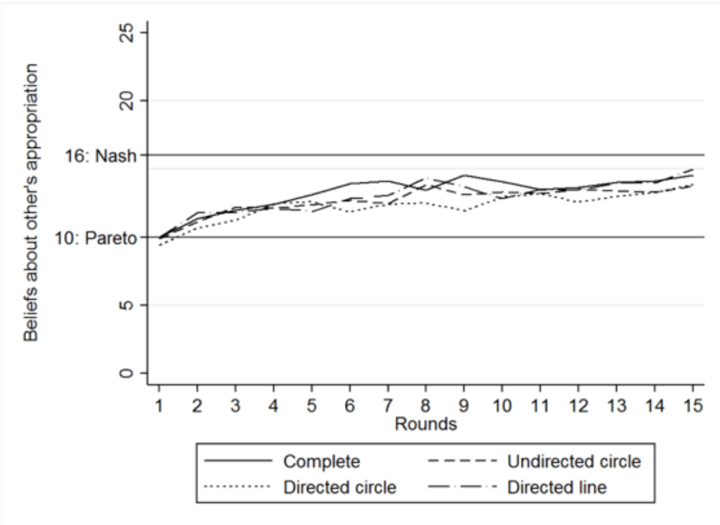


Figure 6.12: Belief's over other's appropriation by node

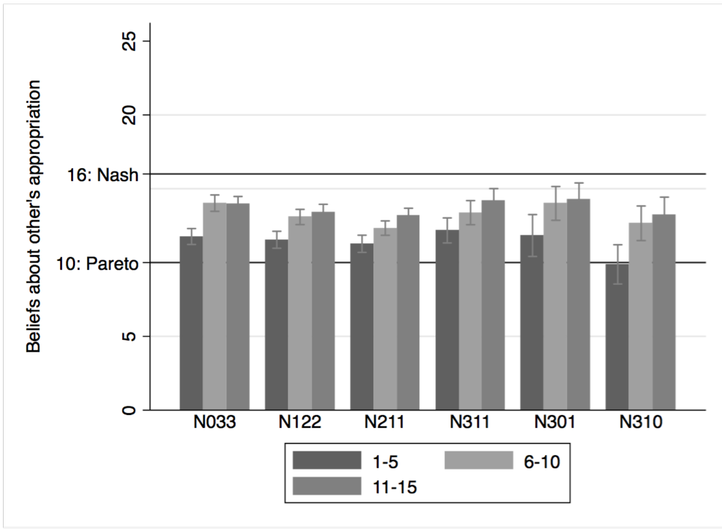


Figure 6.13: Deviation between other's (mean) appropriation and beliefs by network

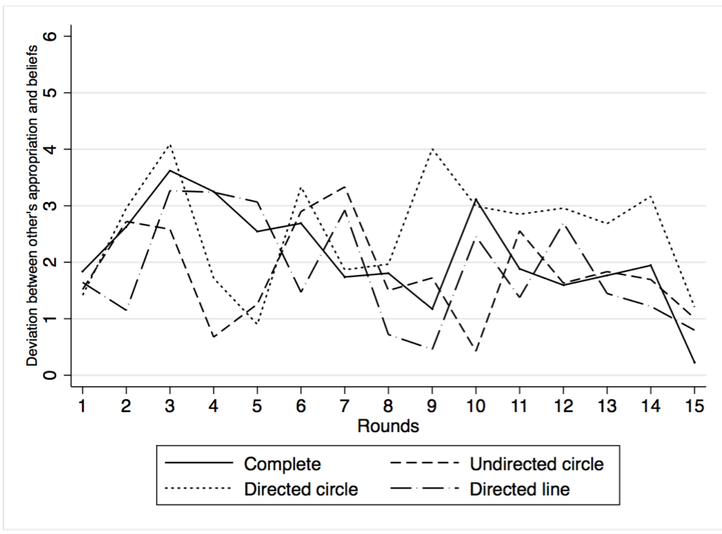


Figure 6.14: Deviation between other's (mean) appropriation and beliefs by node

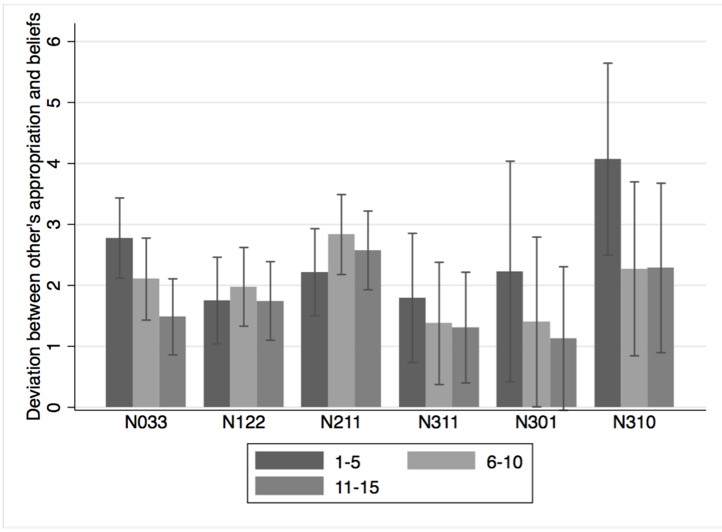


Table 6.5: Difference between beliefs and other's (mean) appropriation across nodes

Outcome:	Deviation between beliefs and other's (mean) appropriation	
Random-effects models:	(1)	(2)
Node degree = 1, N122	0.013	-0.715
	(0.78)	(0.92)
Node degree = 2, N211	1.388*	0.408
	(0.82)	(0.89)
Node degree = 3, N311	1.032	0.678
	(1.11)	(1.27)
Node degree = 4, N301	1.137	1.125
	(1.00)	(1.64)
Node degree = 5, N310	2.662***	3.202***
	(1.02)	(1.18)
Period = 1, Rounds 6-10	-0.293	-0.673
	(0.25)	(0.44)
Period = 2, Rounds 11-15	-0.613**	-1.293***
	(0.27)	(0.35)
N122 X Rounds 6-10		0.897
		(0.68)
N122 X Rounds 11-15		1.286**
		(0.64)
N211 X Rounds 6-10		1.290**
		(0.60)
N211 X Rounds 11-15		1.650**
		(0.66)
N311 X Rounds 6-10		0.254
		(0.83)
N311 X Rounds 11-15		0.805
		(0.92)
N310 X Rounds 6-10		-0.155
		(1.45)
N310 X Rounds 11-15		0.193
		(1.64)
N301 X Rounds 6-10		-1.127
		(0.95)
N301 X Rounds 11-15		-0.492
		(0.99)
Sex	0.525	0.525
	(0.41)	(0.42)
Experience	0.426	0.426
	(0.28)	(0.28)
Economics	-1.412***	-1.412***
	(0.45)	(0.45)
Constant	1.241	1.595**
	(0.77)	(0.79)
Observations	2,880	2,880
Number of subject	192	192
Session dummies	Yes	Yes
Individual controls	Yes	Yes

Notes: Robust standard errors are clustered at the subject level, and *** p<0.01, ** p<0.05, * p<0.1. The Complete network is the omitted category. The Complete network and period 1 (rounds 1-5) are the omitted categories.

Chapter 7

Conclusions

Understanding and changing human behaviour is crucial to tackling the multiple environmental challenges facing us today. In this spirit, this thesis seeks to advance our knowledge of the individual and situational factors driving human behaviour in three contexts: contributions towards protecting public goods like biodiversity and the environment, choices under risk from environmental externalities like air pollution, and cooperation over shared common pool resources. Each of the five papers uses experimental methods to provide sharper causal insights to behavioural impacts of information and incentives or to extract preferences and beliefs in the settings considered.

In this concluding section, I summarise the key result from each paper. After this, I briefly discuss some overarching concerns that span across the papers which stem from the methodology of lab and lab-in-the-field experiments, and propose ways to address this in future the context papers in this thesis. I note that each paper contains its own conclusion which has more specific discussions relating to the themes in the paper.

Paper 1 explores the direct impact of different types of audiovisual information through the charismatic megafauna and outrage effect on contributions to biodiversity conservation. It also signals that mixed emotions could be drivers of pro-sociality in the conservation context. Paper 2 charts the indirect spillover effects of these video interventions on subsequent pro-environmental behavioural intentions. Taken together, the papers highlight the potential of the narratives in videos to encourage public engagement and conservation action to address the sixth mass extinction event.

Papers 3 and 4 explore the psycho-social determinants of avoidance behaviours amongst active travellers, namely cyclists in London. In Paper 3, risk perception rather than risk preferences seems to be a better predictor of avoidance behaviour in the context and sample studied. Domain-specific risk preferences via the willingness to take health risks showed more behavioural validity as regards risk-taking while cycling, and the evidence for cross-context validity was not strong. Paper 4 showed that underlying beliefs about air quality determine how individuals respond to social norm messaging. These results collectively suggest that subjective beliefs about environmental risks influence choice under uncertainty in the context of air pollution avoidance.

Paper 5 explores how the peer monitoring and punishment network structure affects cooperation in a commons dilemma. The results suggest that while free-riders (i.e., those who extracted from the CPR at a level above the Pareto optimal appropriation) were punished in all networks, incomplete connected networks like the undirected and directed circle elicited lower punishment towards those who appropriated less than the socially efficient level, at least in the short-run. These punishment patterns leave the complete network as the least efficient because the net payoffs after punishment are the lowest. Although individuals are initially optimistic about others pro-sociality across networks, beliefs converge to the selfish equilibrium more rapidly in complete networks. These findings open up new questions about how the underlying socio-spatial network of interactions and information feedback affects how people learn to cooperate to manage shared natural resources.

En masse, these papers attempt to make a modest contribution to the growing body of work that constitutes behavioural environmental economics. The papers take advantage of the tight control afforded by the lab to testbed novel interventions or the lab validated protocol to recover preferences in the field. That said, there are concerns that findings from lab experiments may not generalise to real-life settings. This is eloquently discussed in Levitt and List (2007b) and Levitt and List (2007a). They question if the critical assumption underlying the interpretation of data from lab experiments is defensible, i.e., if insights gained from lab experiments can be extrapolated to the world beyond. They argue that the level of scrutiny by the experimenter, the lack of subject anonymity, the artificial context, the (most often monetary) stakes, and the population (mainly students), all deviate significantly from real-world settings.

There has been a lively debate over these issues, with Camerer (2011), Falk and Heckman (2009) and Kessler and Vesterlund (2015) amongst others who counter-argue that lab experiments are particularly useful to isolate general principles and qualitative relationships between variables, rather than quantitative effects (e.g. direction of the effect, rather than the precise effect size). This emphasis on qualitative results is useful in part because it acknowledges that all theoretical and empirical models require simplifying assumptions, which makes it unlikely that the effect size will be accurately captured anyway (Kessler and Vesterlund, 2015). It is in this spirit that we look to interpreting the results of Paper 1, 2 and 5.

Another means to increase external validity is to design lab experiments to mirror the environment being studied. This strategy was adopted in Papers 1 and 2, which tried to bring in more context into the lab: for example by using different design innovations (e.g. providing donation receipts), framing the issue explicitly in environmental terms with adequate detail, and collecting post-experimental survey data about subject motivations to uncover alternative explanations. Moreover, the behaviour of those enrolled in university labs is of interest to charity organisations aiming to conserve biodiversity in the global south, precisely because it targets these populations in their outreach work.

Nonetheless, the debate is far from settled.[1] Most relevant to the work in this thesis are the concerns about external validity about experimental games attempting to measure social preferences. Galizzi and Navarro-Martínez (2018) illustrate this by undertaking a meta-analysis of studies that connect choices in social preference games to field-based behaviours. They find that only 39.7% of the reported lab-field correlations and 37.5% of the reported lab-field regressions find a statistically significant association between games and field behaviours. There was a weak correlation between lab-field based behaviours: the overall average correlation of all papers was 0.14, and in the papers that report significant correlations it is 0.27.

In Papers 3 and 4, I sought to increase external validity by moving from the lab into the field. That said, there are still some concerns, as I ultimately rely on a convenience sample as subjects need to select into participating in the experiment, and the subjects know they are participating in an experiment, which may, in turn, change their behaviour (as observed in (Levitt and List, 2011) and Gosnell et al. (2016)).

There are some significant methodological implications for future work. The first is that replications of the papers in the lab and online platforms, amongst bigger and more diverse samples and varied environments, will reveal the robustness of the results. This may be especially useful in the case of Paper 3 to recover risk and other preferences using a larger and more representative sample of cyclists, and even other active travellers. Papers 1 and 2 would also benefit from replication exercises.

Another direction is to experimentally test these interventions in the field, using a combination of natural and framed field experiments. For instance, an exciting prospect

[1]This discussion also follows some contours of the 'replication crisis' in social psychology. See OpenScienceCollaboration (2015), who report that only one-third to one-half of the original findings in high-ranking psychology journals were also observed in the replication study, and Gilbert et al. (2016) for a counter-argument.

for Paper 1 would be to work with a partner to implement a natural field experiment, one who is willing to implement the proposed design (e.g. narrative content into the film) and provide the data needed to estimate the causal effects of interest. Conducting this work both in countries with conservation sites and donor countries could be fascinating work. Implementing social norms messaging using a natural field experiment could also be a possibility for Paper 4, perhaps with the use of observational or revealed data depending on a refinement of the outcome variable (Lawrence, 2015; Allcott, 2011).

To delve deeper into the dynamics of behavioural spillovers and take the results of Paper 2 forward, future research could employ a more mixed-methods approach. This could entail combining experimental interventions with diary-based methods or a lab-field study to track the evolution of multiple behaviours over a longer time horizon and across different domains (e.g. in Carrico et al. (2017) and Dolan and Galizzi (2014)). This could even be used to examine the effects of information and incentives in conservation projects in the field in transitional countries and those rich in biodiversity resources. For e.g. Alpízar et al. (2017) looks at 'behavioural leakages' from targeted incentives.

For Paper 5, an innovative approach would be to combine detailed social network data about multiple relationships, revealed behaviour in experimental games, and actual resource management outcomes. For e.g. Chandrasekhar et al. (2012) use a framed field experiment with real network data to uncover social learning dynamics. While it was not financially feasible to carry out these proposed projects over the course of this doctoral dissertation, they are a promising way forward to build on the research contained in this thesis.

In moving from the lab to natural field experiments one has to keep in mind their primary limitation, i.e., they may not be external valid in other field settings. This has been called the 'transportation problem' by Deaton (2010). It is not dissimilar to the notion of 'parallelism' referred to in Smith (2010). Ultimately an imaginative use of a combination of experimental methods is the key to advancing our knowledge of people's decisions to protect the environment and protect themselves from environmental risks.

Bibliography

Allcott, H. (2011). Social norms and energy conservation. *Journal of public Economics*, 95(9-10):1082–1095.

Alpízar, F., Nordén, A., Pfaff, A., and Robalino, J. (2017). Spillovers from targeting of incentives: Exploring responses to being excluded. *Journal of Economic Psychology*, 59:87–98.

Camerer, C. (2011). The promise and success of lab-field generalizability in experimental economics: A critical reply to levitt and list. Technical report, SSRN. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1977749 [Access date: 20 March 2018].

Carrico, A. R., Raimi, K. T., Truelove, H. B., and Eby, B. (2017). Putting your money where your mouth is: An experimental test of pro-environmental spillover from reducing meat consumption to monetary donations. *Environment and Behavior*, page 0013916517713067.

Chandrasekhar, A. G., Larreguy, H., and Xandri, J. P. (2012). Testing models of social learning on networks: Evidence from a framed field experiment. *Work. Pap., Mass. Inst. Technol., Cambridge, MA.*

Deaton, A. (2010). Instruments, randomization, and learning about development. *Journal of economic literature*, 48(2):424–55.

Dolan, P. and Galizzi, M. M. (2014). Because i'm worth it: a lab-field experiment on the spillover effects of incentives in health. Technical report, Centre for Economic Performance, London School of Economics and Political Science.

Falk, A. and Heckman, J. J. (2009). Lab experiments are a major source of knowledge in the social sciences. *science*, 326(5952):535–538.

Galizzi, M. M. and Navarro-Martínez, D. (2018). On the external validity of social preference games: a systematic lab-field study. *Management Science.*

Gilbert, D. T., King, G., Pettigrew, S., and Wilson, T. D. (2016). Comment on "estimating the reproducibility of psychological science". *Science*, 351(6277):1037–1037.

Gosnell, G. K., List, J. A., and Metcalfe, R. (2016). A new approach to an age-old problem: solving externalities by incenting workers directly. Technical report, National Bureau of Economic Research.

Kessler, J. and Vesterlund, L. (2015). The external validity of laboratory experiments: The misleading emphasis on quantitative effects.

Lawrence, N. K. (2015). Highlighting the injunctive norm to reduce phone-related distracted driving. *Social Influence*, 10(2):109–118.

Levitt, S. D. and List, J. A. (2007a). On the generalizability of lab behaviour to the field. *Canadian Journal of Economics/Revue canadienne d'économique*, 40(2):347–370.

Levitt, S. D. and List, J. A. (2007b). What do laboratory experiments measuring social preferences reveal about the real world? *Journal of Economic perspectives*, 21(2):153–174.

Levitt, S. D. and List, J. A. (2011). Was there really a hawthorne effect at the hawthorne plant? an analysis of the original illumination experiments. *American Economic Journal: Applied Economics*, 3(1):224–38.

OpenScienceCollaboration (2015). Estimating the reproducibility of psychological science. *Science*, 349(6251):aac4716.

Smith, V. L. (2010). Experimental methods in economics. In *Behavioural and Experimental Economics*, pages 120–136. Springer.

Appendix A

Literature Appendix for Chapter 1

In this Appendix to Chapter 1, I locate the essays in this thesis and their contributions, within the fast-growing sub-discipline of behavioural environmental economics. The objective of this effort is to ground this thesis in the broader trends in the discipline to provide historical context to my work. Please refer to the introduction for a more concise version of the key contributions, and each paper for a more specific discussion of the conceptual themes, methods and results.

In the first part, I propose that standard environmental and resource economics that has been traditionally preoccupied with 'market failure', which is commonly conceptualised as departures from the ideal of the perfectly competitive market. The conventional analysis rests on the foundational assumption the rational actor model of human behaviour. In the second part, I sketch the ascent of behavioural economics, which has emphasised 'behavioural failures', often defined as systematic deviations from this standard rational choice model. In the third section, I note that it is particularly conducive - and necessary - to apply behavioural insights to explain human decision-making in environmental dilemmas. By dwelling on how research at the intersection of market and behavioural failures is crucial, I extend Shogren and Taylor (2008)'s earlier analysis of the same themes by focusing on the work presented in this thesis. Then, I situate each essay and its contributions within three distinct but interrelated strands of literature, firstly about people's choices to protect and value public goods, secondly about choices under environmental risk, and thirdly on cooperation and social dilemmas over shared natural resources.

A.1 Market failures and Environmental economics

The field of Environmental and Resource Economics grew swiftly from the 1960s onwards in response to mounting concerns over the ecological limits of economic activity (Boulding, 1966), rapidly depleting renewable resources such as fish stocks and tropical forests, and scarcity of non-renewable resources reflected in soaring oil prices towards the end of the 1970s (Gordon, 1954; Hardin, 1968; Dasgupta and Heal, 1979). Environmental movements contesting the adverse health and wellbeing effects of environmental pollution, exemplified in Rachel Carson's evocative account of the effect of agrochemicals in Silent Spring (Carson, 2002), further spurred the field to explore the social welfare implications of anthropogenic environmental degradation.

Market failure – or the deviations from the conditions of an ideal competitive economy, due to factors like missing markets, externalities, public goods or absent property rights – is a fundamental organising concept commonly applied to the consumption side in the field (e.g. in Arrow (1969), Kolstad et al. (2011) and Perman et al. (2003)). But the economic welfare implications of market failure and resource scarcity have long been a staple of microeconomic theory within the neoclassical paradigm, which is the intellectual precursor of the environmental and resource economics, as illustrated in works of Pigou on externalities and taxation (Pigou, 1920), Kaldor and Hicks on welfare economics (Kaldor, 1939; Hicks, 1939) or Hotelling on the optimal rate of resource use (Hotelling, 1931).[1]

Within this conceptual framework, the standard assumption in environmental economics was that individuals act in a manner prescribed by rational choice and expected utility theories in choosing whether to protect the environment or themselves from environmental risk. Bernheim and Rangel (2007) offer a succinct summary of the central assumptions of the standard model. They note that individuals are believed to have well-defined preferences rankings over different states of the world that rest on the following assumptions: (i) preferences are coherent and well-behaved, (ii) the domain of an individual's preference rankings is the set of lifetime state-contingent consumption paths, (iii) fixed over an individual's lifetime and states of nature, and (iv) the most preferred alternatives are chosen from a given choice set (utility maximising), and individual makes

[1] Heal (2007), Pearce (2002), and Cropper and Oates (1992) provide more detailed historical perspectives about the evolution of environmental and resource economics and it's core areas of inquiry, including debates about sustainable development and it's measurement, natural capital and economic valuation, discounting, and policy appraisal and cost-benefit analysis. While environmental and resource economics remained strongly rooted in the neoclassical paradigm, ecological economics, which emerged around the same time, was more interdisciplinary and emphasised the ecological limits of growth, as discussed in Daly's steady state economics (Daly, 1973). Spash (2012), Røpke (2005) and Røpke (2004) discuss the foundations and historical origins of the ecological economics as a distinct field.

no mistakes. These standard preferences are revealed through individual choices, which are made subject to a budget constraint. Furthermore, revealed preferences are thought to represent an agent's actual interests or their 'normative' preferences (Beshears et al., 2008).

The social cost of market failures provides an argument for government intervention through environmental policy. Altering an agent's budget constraint by modifying their incentives, was seen as the primary policy conduit to internalise the external (environmental) benefits and costs, to ultimately increase social welfare efficiently. Consequently, policy solutions commonly advocated by economists to correct market failure included the allocation of property rights (especially to privatise open-access 'commons') (Hardin, 1968; Coase, 1974), and market or incentive-based instruments aiming to price externalities through Pigouvian taxes or subsidies, and tradeable permits (Dales, 1968; Stavins, 2003). Comparisons between conventional command-and-control regulations and incentive-based mechanisms repeatedly noted that the former failed to achieve environmental objectives in the least-cost manner (Hahn and Stavins, 1992). Alternately, improving access to more accurate or complete information would allow individuals to revise their preferences (if they so wish) over available choice alternatives.

In a nutshell, the standard assumption in environmental economics is that individuals would behave 'as if' they were rational actors in their responses to incentives and information to correct market failures, which in turn would achieve environmental protection at least cost. This standard approach follows Friedman and Savage (1948)'s famous argument for adopting a 'positive' methodological approach in economics and retaining the (unrealistic) rational actor assumptions. They used the analogy of an expert billiards player who made his shots *as if* he calculated the expected trajectory of the ball based on complicated formulas, although these calculations were only approximated in a split second before play.

A.2 Behavioural failures and Behavioural economics

Mounting evidence from behavioural economics has catalogued systematic deviations in preferences, beliefs and choices, that violate the predictions of the rational actor model (DellaVigna, 2009). Studies in this field aim to offer a more realistic description of human behaviour by incorporating insights from social and personality psychology, and more recently sociology and anthropology, to replace *Homo economicus* ('Econs' or 'the rational economic man') with *Homos sapiens* ('Humans') (Thaler, 2000). The method of experimentation was, and remains, a principal means to change thinking about economics because it enabled discussions about the conditions under which standard models were falsified or verified. Importantly, systematic deviations in revealed preferences across different contexts (e.g. knowledge and resources) and institutions (e.g. rules governing socio-economic interactions) was quantified in a controlled and replicable manner (Smith, 1989). Indeed economic experimentation has been critical to advance our understanding of human behaviour in environmental dilemmas, as discussed in section 1.3 in more detail (Ostrom, 2006; Janssen et al., 2010; List and Price, 2016).

Mullainathan and Thaler (2000) distil three traits that offer a more realistic picture of individual decision-making compared to the standard model: bounded rationality, bounded willpower and bounded selfishness. Bounded rationality reflects that humans have limited cognitive capacity that constrains problem-solving (Simon, 1955). People often make biased probability judgements, are averse to loss and appear overconfident. They rely on heuristics or rules of thumb in their decision-making, and seem to anchor their judgements and choices on the status quo or potentially irrelevant information (Tversky and Kahneman, 1986; Kahneman et al., 1982; Kahneman and Tversky, 1979; Ross and Nisbett, 2011). Bounded willpower refers to the tendency for people to take decisions that run counter to their long-run interest. This is often captured by time-inconsistent preferences, where measured discount functions decline at a higher rate in the short run than in the long run (also called present-biased preferences), and is often captured through hyperbolic utility discounting (Chabris et al., 2010). Time-inconsistent preferences have been linked to self-control problems and rash decision-making, such as addictions and procrastination (Laibson, 1997; DellaVigna and Malmendier, 2006). Lastly, bounded self-interest refers to the idea that individuals care or act as if they care about other's wellbeing. They care about fairness, and take personally costly altruistic, reciprocal and even spiteful decisions, contrary to the assumption of the rational pursuit of self-interest (Fehr and Gächter, 2000; Fehr and Schmidt, 2006). These anomalies or behavioural biases, defined against the benchmark standard rational choice model, are often grouped under the term 'behavioural failures' (Shogren and Taylor, 2008).[2]

There are also attempts to present a more cogent picture of how decisions are made. For example, dual processes theory emphasises two distinct 'systems' operating in the

[2]Thaler (2016) provides a recent overview of the historical roots of behavioural economics. Ashraf et al. (2005) point out that classical economist Adam Smith, the father of economics, adopted a behavioural perspective on economic behaviour in the *Theory of moral sentiments*, by noting the struggle between the 'impartial spectator' and the 'passions' (emotions), morals, and other behavioural anomalies like altruism or fairness (bounded selfishness), overconfidence, inter-temporal decision-making and self-control (bounded willpower) and loss aversion (bounded rationality).

brain, where 'System 1' (or Type 1) processes are fast, automatic, associative, fast, unconscious and affective, and 'System 2' (Type 2) processes, which are slow, controlled, reflective, rule-based, conscious and rational (Kahneman, 2011; Evans, 2008).[3] Accumulating evidence from neuroeconomics shows automatic information processing occurs in distinct brain regions, and highlights the role of affective processes in decision-making and learning (Rangel et al., 2008; Glimcher and Rustichini, 2004). For example, Sanfey et al. (2003) found the anterior insula, an area associated with physical and emotional disgust, was activated amongst individuals who rejected unfair offers in an ultimatum game.[4]

In summary, behavioural economics pays particular attention to people's predictable behavioural failures, the automatic and cognitive processes guiding human decision-making, and situational factors in the decision context. Behavioural failures provide an argument for policy-makers to help individuals avoid mistakes by changing the context in which humans make decisions (e.g. changing defaults), the way or type of information provided (for e.g. combining social comparisons), and the way incentives are designed (e.g. combining incentives with social comparison information as a default), as a complement to traditional command-and-control, information and incentive-based regulations to promote social welfare. This approach is illustrated in the 'Libertarian paternalism', which advocates changing the context or the 'choice architecture' to 'nudge' people to take better decisions (Thaler and Sunstein, 2008) and the MINDSPACE approach to changing behaviour (Dolan et al., 2012). Behaviourally informed interventions have caught the imagination of policymakers: while the UK, Germany, and the USA established first 'nudge' units at the national level, now, over a dozen countries today have them or are actively incorporating behavioural insights into the formulation of policy (Afif, 2017). Croson and Treich (2014) note that the popularity of nudges arises from their cost-effectiveness, propensity to be tested through experimentation in the field (in which they seem to perform well), and lack of strong objections on the basis of fairness and cost concerns (as they can be applied equally to everyone, versus polluters or victims of pollution).[5] The

[3]A counter-perspective is offered by Gerd Gigerenzer, and others, who propose that non-standard decision processes like heuristics evolved in humans to allow us to take 'fast and frugal' rule-based decisions under uncertainty, and that single process accounts of decision-making are sufficient to account for observed empirical patterns of decision-making (Gigerenzer and Gaissmaier, 2011). Evans and Stanovich (2013) discuss this debate alongside advances in dual-process accounts of decision-making.

[4]In an ultimatum game, the first player conditionally receives a sum of money and proposes how to divide the sum between herself and another player. The second player chooses to either accept or reject this proposal. Other notable studies include McCabe et al. (2001) on cooperation in trust games, Rustichini et al. (2005) on choice under risk, and McClure et al. (2004) on immediate and delayed monetary rewards.

[5]'Nudges' are interventions that don't impose significant material incentives but can nonetheless steer people in particular directions and also allow for them to go their own way (Sunstein, 2015). The most common objections to behavioural interventions and nudges are that they can violate consumer sovereignty and have unclear welfare foundations. See Sunstein (2015) for a counter-perspective and Schubert (2017) for a discussion on ethics and green nudges.

increasing acceptance of the 'real third way' to regulation (Thaler and Sunstein, 2008), signals a movement away from the rationality assumptions and Friedman's *as if* reasoning, precisely because it fails empirical tests of behaviour, in line with the requirements of the positivist method used in economics (Thaler, 1980).

A.3 Towards a convergent analysis of market and behavioural failures: Behavioural environmental economics

Environmental issues provide a rich terrain for the convergent analysis of market and behavioural failures for several reasons. Natural environments produce a stream of ecosystem services beneficial to humans in the absence of markets. For example, the provisioning of biodiversity enhances ecosystem resilience and regulates climate, and increases human wellbeing through non-use existence and bequest values (Atkinson et al., 2012). This implies that individuals have limited opportunities to gain experience through market-like transactions. Market inexperience has been put forward as a possible explanation for irrational behaviour in environmental settings (see Shogren and Taylor (2008) for a discussion). Correspondingly, market experience has been found to reduce the impact of behavioural biases on behaviour in settings involving the exchange of private goods (List, 2003, 2004; List and Millimet, 2008). But others argue market competition, arbitrage, and learning through experience do not necessarily lead to unbounded rationality, even on theoretical grounds (Mullainathan and Thaler, 2000). Furthermore, Thaler (2016) notes that 'thinking that markets will eradicate aberrant behaviour shows a failure to understand how markets work' (pp. 1585), and notes that firms often devise strategies to profit from self-control problems and cognitive biases.[6] Similar arguments are presented in Akerlof and Shiller (2015) in the context of finance, politics, advertising and sin goods.

Along these lines, Thaler (1980) notes that Friedman and Savage (1948)'s analogy focuses on 'expert' billiards players. Although they may act more rationally with their cumulative experience, understanding and mapping the behaviour of all humans, including intermediates and novices, is arguably as crucial if not more. This need is clearly evident in the environmental domain, where studies have established that public and expert evaluations of risk often diverge (Slovic, 1987), and preferences are heterogeneous

[6] He cited DellaVigna and Malmendier (2006)'s finding of how monthly payments gym - which is more popular - generate higher profits for the gym compared to pay-as-you-go schemes, despite the latter being underutilised by members.

both within and across societies, i.e., people can be selfish, or conditionally or unconditionally cooperative (Fischbacher et al., 2001; Rustagi et al., 2010)), but also have distinct norms for cooperation that rest on local economic patterns of everyday life (Henrich et al., 2001). Understanding behaviour and aggregating preferences across a diverse pool of people are especially relevant to address global environmental challenges like climate change, which is considered 'the greatest market failure the world has ever seen' because of missing markets (Stern, 2008).

Individual contributions to environmental goods and many 'green' consumption behaviours are influenced by a host of standard or self-interested (e.g. if it is cost-saving), and non-standard motivations (e.g., moral or normative motivations if it is the 'right' thing to do, or affective or hedonic motives if it 'feels good'), which impacts individual's beliefs, preferences, and responses to environmental policies (Steg et al., 2014; Bamberg and Möser, 2007; Nyborg et al., 2006). Many existing behaviours are 'grey' by default because consumers do not actively make choices, for example on their electricity providers or printer settings (Egebark and Ekström, 2016; Sunstein and Reisch, 2018). The external costs of these grey behaviours can be persistent due to barriers to change habitual behaviours and aggressive third-party marketing (Kollmuss and Agyeman, 2002; Akerlof and Shiller, 2015; Sunstein and Reisch, 2018).

Moreover, global environmental changes are notoriously complicated, because they stretch across different spatial and time-scales. Effects are unevenly distributed across the current population, many other (often unknown) costs will be borne by future generations. For this reason, the discount rate is pivotal to determine how best to distribute benefits and costs from economic and environmental projects across time and space (Arrow et al., 2013). Concerns about uncertainty (e.g. growth in consumption and returns to investment), ethics, and expert judgement impact the choice of discount rate; but behavioural biases such as time inconsistent preferences additionally complicate policy decisions. Against the standard assumption that individuals/planners discount the future in a dynamically consistent manner, time-inconsistent preferences imply that plans made at one point in time are contradicted by later behaviour (Pearce et al., 2003). Although some note that the case for incorporating inconsistent time preferences into policy evaluation is weak especially if declining discount rates are used (Groom et al., 2005), there are still resource management implications: for example, Hepburn et al. (2010) show that if a planner is unable to commit to policy due to time-inconsistent preferences, the temptation to re-evaluate the plan in future could lead to an inadvertent collapse in the stocks of a natural resource stock.

This brings into focus the uncertainty regarding interactions between and within different components of the socio-economic and biogeochemical systems, and their potential economic and ecological consequences. This uncertainty is epitomised in debates about the magnitude and effects of climate change, or the benefits or rate of loss of biodiversity, suggesting these changes are inherently unpredictable, and the associated 'risks' (i.e., known probabilities over different states of the world) unknowable. Based on this fact, authors like Heal and Millner (2014) argue that the expected utility model, which assumes exogenously given probability distribution over states of the world and preferences over uncertain choices, is a poor match to explain decision-making in these settings.

Finally, most environmental goods and services have public goods or common-pool characteristics and exist across multiple geographical scales, and different (often conflicting) institutional regimes: for example, climate regulation is a global public good and rivers are shared by numerous nation-states and various communities within each (Kaul et al., 1999). Thus, the resolution of environmental problems requires communication and collective action over shared resources between heterogeneous agents under conditions of uncertainty, and even the imminent threat of ecosystem collapse: for example through negotiating environmental agreements over global emissions or water (Barrett, 1994; Carraro et al., 2007; Tavoni et al., 2011; Barrett and Dannenberg, 2012), or peer-based arrangements over local common pool resources (Ostrom et al., 2002; Richter et al., 2013). In these cases, understanding the social dimension of preferences, norms and relationships between agents within their socio-ecological context is critical to facilitate cooperation (Ostrom, 2000; Sethi and Somanathan, 1996).

In fact, the issues discussed above align with the five factors that Beshears et al. (2008) call 'red flags' because they increase the likelihood of a wedge between revealed and normative preferences and lead to bounded rationality: passive choice, complexity, limited personal experience, third-party marketing, and inter-temporal choice. Consequently, environmental policies that aim to correct market failures may go awry or be ineffective at achieving its objective if it ignores behavioural failures or is based on inappropriate models of the standard rational agent (Hepburn et al., 2010). Going further, behaviourally informed environmental policy may result in more protection at lower costs (Shogren et al., 2010).

In light of this, I contend that both market and behavioural failures must inhabit the minds of policy-makers and academics to glean rigorous insights into human behaviour in environmental settings. Support for this stance and the need to have a more realistic picture of human behaviour for environmental policy is reflected recent efforts to consolidate relevant studies under the umbrella 'behavioural environmental economics' over the past decade. I refer the reader to the following review papers for emerging debates in this rapidly growing sub-discipline: Dasgupta et al. (2016), Croson and Treich (2014), Hammitt (2013), Carlsson and Johansson-Stenman (2012), Shogren et al. (2010), Shogren and Taylor (2008), Venkatachalam (2008), and Gowdy (2008), and a special volume in the *Environmental and Resource Economics* journal in 2010.

However, neither the call for more research at the intersection of behavioural and market failures nor apprehensions regarding the suitability of the rational actor model to explain behaviour in environmental settings, are new. Indeed, some of the earliest writings that systematise behavioural failures does so within the context of market failure via non-market valuation using stated preferences (SP) methods. Knetsch and Sinden (1984) experimentally demonstrated that the divergence between the stated willingness to pay (WTP) and willingness to accept (WTA) persisted even with the use of actual money payments and compensations, and in market transactions where individuals could bargain to test the predictions of the Coase theorem (Kahneman et al., 1990). Behavioural explanations put forward to explain the WTP-WTA divergence included anomalies like the endowment effect, loss aversion and the status quo bias (Kahneman et al., 1990).[7] Likewise, there are also methodological similarities between experiments and stated preference studies, as evident in the use of experimental methods to test values elicited from hypothetical surveys (Carlsson, 2010). A challenge to the dominance of the rational actor model also came from Ostrom et al. (1992) and others, who were experimentally illustrating bounded self-interest through and brought to light cases where self-governance of the commons was possible.

This is much like the two-way traffic between environmental economics and behavioural economics noted by Heal (2007), who highlighted the environmental contributions made by leading economic thinkers, such as Vernon Smith, Kenneth Arrow, and Joseph E. Stiglitz amongst others. A similar argument can be made to illustrate the interconnections between environmental and behavioural economics, by thinking of those whose research advanced both fields and went on to win the The Sveriges Riksbank Prize in Economic Sciences, including Vernon Smith, Elinor Ostrom, Daniel Kahneman, and Richard Thaler, for their direct contributions to the discipline as previously discussed in the body of this essay, as well as Amartya Sen (for his work on sustainable human development, well-being and famines), Jean Tirole (who has worked on inter-linked issues such as self-image and moral motivations, social norms, motivated reasoning, apart from

[7]The endowment effect refers to the increased value of a good to an individual when the good becomes part of the individual's endowment. This effect is seen as a manifestation of loss aversion, which is the generalisation that losses are weighted substantially more than objectively commensurate gains. Status quo bias refers to the tendency for people to adhere to the status quo because the disadvantage of leaving it looms larger than the benefits of doing so (Kahneman et al., 1991).

energy, climate change and environmental regulation), and Thomas C. Schelling (a pioneer in strategic analysis using game theory, which is used extensively to study behaviour environmental dilemmas, and who has also written on climate change). Despite these early intellectual connections, there is still scope for a more considerable convergence in behavioural and environmental economics in several areas, including contributions to and cooperation over shared natural resources, and choices under environmental risks (Ostrom, 1998; Shogren et al., 2010; Carlsson and Johansson-Stenman, 2012). The research in this thesis attempts to bridge some of these gaps. It is inspired by and draws on existing research at the intersection of environmental and resource economics, and behavioural economics in a series of five papers using experimental methods as described below in more detail.

A.4 Locating the papers in existing debates

In the following sections, I locate each paper within the larger debates and existing gaps in the literature to outline it's key contributions.

A.4.1 People's choices to protect and value biodiversity, and the environment: Papers 1 and 2

Global biodiversity loss is arguably one of the most urgent and intractable market failures facing us today. Through an economic lens, it can be conceptualised as a case of complex multiple overlapping public goods across different scales, because various species are located in ecological niches within their natural habitats, which in turn can be aggregated into different ecosystems. Given this, market prices - if present at all - are poor reflections of the underlying value of these assorted public goods. Consequently, biodiversity is under-provisioned as reflected in the rapid and irreversible sixth mass extinction event (Ceballos et al., 2015). But as noted by Helm and Hepburn (2012), the question of resource allocation towards biodiversity has been largely ignored by mainstream economics despite the urgency of the issue.

There are arguably economic and ecological arguments to conserve biodiversity due to the range of ecosystem, climate regulation, and wellbeing benefits it offers, besides the ethical case for protection based on its intrinsic value (Polasky et al., 2012).[8] Economic

[8] Other studies highlight leveraging co-benefits from conservation, poverty alleviation, and development through market-based schemes like payment for ecosystem services and bioprospecting (Ferraro and Hanauer, 2014; Palmer and Di Falco, 2012).

arguments largely rest on how the net benefits of biodiversity are valued. Monetary values are estimated through either revealed (e.g. travel cost) or more commonly stated preference methods. As a case in point, Bartkowski et al. (2015) reports that more than 80% of the studies applied either contingent valuation (CV) or choice experiments (CE) to value biodiversity, in a comprehensive survey. From a policy perspective, valuing species conservation enables their inclusion in resource allocation decisions by ranking them against competing for economic projects, allows for (possible) compensation, and most critically communicates conservation needs in the language of economics which can be persuasive to a wider (sometimes sceptical) audience (Atkinson et al., 2012).

However, several limitations to stated preference methods exist, many of which stem from their inherent vulnerability to behavioural biases, not unlike other survey-based methods. An interlinked issue is that the way and type of information provided to the subjects influence their responses. Apart from the WTP-WTA disparity discussed briefly in the previous section, the classic debate around the embedding effects and scope insensitivity also illustrate this. Kahneman pointed out that the WTP increased taxes to prevent the drop in fish populations in all Ontario lakes was only slightly higher than the WTP to preserve the fish stocks in only a small area of the province, by Toronto residents, whereas we may expect that the WTP should have been higher (in Kahneman and Knetsch (1992)).[9]. Another quintessential albeit under-explored finding is that including information about intentionally caused ecological harm by humans in CV scenarios elicited higher WTP compared to the damage caused by nature. As people reported feeling more upset and interested, this empirical result was termed the 'outrage effect' (Kahneman et al., 1993).

These and other anomalies lead to debates about the ability of CV method to capture 'true' preferences or WTP for conservation on the basis that stated WTP expressed environmental attitudes and ideological values, the purchase of moral satisfaction, or the 'warm glow' from contributions instead. A core concern voiced by Kahneman and Knetsch (1992) and others like Diamond and Hausman (1994) was that CV respondents tend to disregard the characteristics of the public good – like it is magnitude – because they have a certain amount they are prepared to contribute. While subsequent methodological advances such as the split sample scope test have addressed this issue, debates around these questions are not settled. Carson (2012) notes that scope insensitivity is more likely when a program is seen to provide multiple outputs, such as protecting different endangered species. A fundamental challenge is to operationalise ecological science and the many

[9]See Carson (2012) and Kling et al. (2012) for excellent discussions on recent advances in the debates on contingent valuation, including in relation to neoclassical economics, and Hausman (2012) for a critical counter-perspective.

definitions and measures biodiversity within an economic valuation framework because it directly affects the valuation of benefits (Nunes and van den Bergh, 2001; Bartkowski et al., 2015).

Instead of using SP methods or existing administrative data (e.g. in Metrick and Weitzman (1998)), Paper 1 approaches these questions from a new angle by using an incentive-compatible charitable giving game to explore people's choices to protect biodiversity using a series of lab experiments. This allows us to study the robustness of the 'charismatic megafauna effect' and the 'outrage effect' in a new type of decision setting, and with new informational interventions. It also allows us to check whether complex habitats composed of both species elicit systematically different pro-social revealed preferences. It additionally maps the causal effect of narrative-based audio-visual information, and a non-pecuniary incentive of the public recognition of donors also impacts donations, as this is strategy commonly employed by charitable organizations (Karlan and McConnell, 2014).

The potential for audio-visual media as an instrument for behaviour change is clear from Paper 1, and numerous other studies which have the causal effect of movies on other behaviours including voting turnout and preferences, fertility choices, even migration decisions (DellaVigna and La Ferrara, 2015). But more empirical evidence is required in the environmental domain. Most studies consider effects on climate documentaries by using before-after surveys to look at changes in range of self-reported environmental behaviour and intentions, attitudes, and beliefs (Howell, 2011). While promising and novel, they are prone to endogeneity and sample selection concerns, thus complicating causal inference of the movie on actual behaviour (Howell, 2014). A notable exception is Jacobsen (2011), who uses a difference-in-difference specification to show an increase in carbon offset purchases of about 50 percent relative to the baseline for individuals living within 10 miles of a theatre showing *An Inconvenient Truth*. Moreover, most studies moreover focus on movie exposure rather than content because exogenously varying content while holding exposure constant (or a corresponding causal identification strategy) is challenging in field settings. Another open question, is whether behavioural change persists in the long-run and the factors underpinning these behavioural dynamics: both Jacobsen (2011) and Howell (2011) find that the increases in revealed and self-reported environmental behaviour wash out over time.

Paper 2 builds on Paper 1 to investigate some of these questions and reports results of a companion lab experiment. We analyse if watching biodiversity conservation videos (with exogenously varied exposure and content) and donating, has unintentional spillover effects on an individual's the subsequent willingness to pay a green fee (WTP fee), and the willingness to donate time to an environmental campaign (WTD time). Our contributions are as follows. First, we add to the literature on media effects on environmental behaviour by attempting to measure both the direct and indirect causal short-run effects on different environmental behaviours and intentions. Second, we adopt a spillovers framework, which pays special attention to the sequential nature of behaviour, and thus maps out potential positive, negative or no spillovers. In this way we contribute to the spillovers literature by looking at the unintentional pro-environmental consequences of media interventions, rather than text or graphic information or incentives (see Dolan and Galizzi (2015) and Truelove et al. (2014) for surveys).[10] Third, we attempt to disentangle some of the mechanics behind the spillover effects, by considering whether behavioural similarity and subject pro-sociality, i.e., if they were past donors, affect the direction and magnitude of any spillover effect. This builds on the nascent findings in environmental psychology, which flag these as probable but under-examined factors that influence spillover effects (Whitmarsh and O'Neill, 2010; Margetts and Kashima, 2017).

To sum up, Papers 1 and 2 contribute to the behavioural environmental economics literature by attempting to unpack factors driving people's choices to protect biodiversity, and identifying potential pathways to increase pro-socially. They highlight that people's choices could be influenced through innovative informational interventions like audio-visual media, and careful attention needs to be paid to the narratives and stories presented in them, given the direct and indirect effects that they have on behaviour, and the emotional reactions they elicit in audiences. Also, pre-existing differences across individuals (e.g. demonstrated pro-sociality through donations outside the lab) determine responses to these interventions, and the extent to which behavioural spillovers occur. The methodological approach, results, potential limitations, and way forward are discussed in Chapter 2 and 3 for Papers 1 and 2 in more detail.

A.4.2 People's choices to protect themselves from air pollution: Papers 3 and 4

Poor air quality from air pollution is another pressing challenge which has adverse effects on human health and well-being, which exacerbates other environmental problems like climate change. It can be conceptualised as a negative externality and public bads problem arising from the excessive release of pollutants like Carbon monoxide (CO), Nitrogen oxides (NOx), and other particulate matter (PM) into the atmosphere from diffuse sources. Worldwide, over 80% of people in urban areas lived in places where air quality levels were

[10]Conventionally unintentional behavioural spillovers of media content have been used to elicit incidental emotion states (Dolan and Galizzi, 2015).

deemed harmful by the World Health Organization, and 59% of the U.K. population lives in areas where the level of air pollution is above the legal limits by some estimates (Laville, 2017). The adverse effects of polluted air have been linked to the higher likelihood of traffic accidents (Sager, 2016), lower test scores (Ebenstein et al., 2016), poorer cognitive function (Clifford et al., 2016), reduced subjective well-being including life satisfaction and happiness (Dolan and Laffan, 2016), and even suicide attempts (Szyszkowicz et al., 2010), apart from detrimental long-term and short-term health metrics like increased mortality risk, cardiovascular and respiratory illnesses (Pope III et al., 2009; Currie et al., 2014). Vehicular traffic is a crucial contributor: on average, transport is responsible for one-quarter of the PM in the air. Keeping in mind that emissions need to be curbed on the supply side, a fundamental question on the demand side is what motivates people to protect themselves by reducing exposure or avoiding air pollution?

Economic research has placed a considerable focus on understanding avoidance behaviour, which is conceptualised as a type of preventive health behaviour undertaken by individuals to reduce their exposure to environmental pollutants. Zivin and Neidell (2013) note that ignoring the costly (in money and effort terms) actions individuals take to protect themselves is problematic on three fronts. It can cloud pure biologic signals in epidemiological research and lead to mischaracterizations of the welfare function in economics. Encouraging avoidance through informational approaches is also an important policy lever to empower citizens to take better decision to enhance their health and wellbeing. That said, the bulk of literature on avoidance focuses on the effects of information alerts on extreme pollution or smog days and their behavioural effects on reducing outdoor activity (Zivin and Neidell, 2009; Janke, 2014; Saberian et al., 2017). There is limited research on the 'everyday' avoidance choices taken by individuals to self-protect against daily exposure or the psychological mechanisms underpinning individual these avoidance decisions, both of which are crucial to painting a more comprehensive picture of individual avoidance behaviour.

Expected utility theory (EUT) is foundational for how environmental economists think about valuing and controlling risks to health and the environment. In this framework, the degree of risk aversion is commonly put forward to explain inter-individual differences in the propensity of individuals to take risks or conversely protect themselves by engaging in preventive health measures. But insights from behavioural economics show that the EU model performs poorly in describing choices under risk: for instance, people overestimate the likelihood of suffering from low probability but serious events but underestimate high probability events (e.g. aeroplane versus car accidents) (Tversky and Kahneman, 1992). While some alternatives have been proposed, most notably cumulative prospect theory (Tversky and Kahneman, 1992), they are yet to be widely incorporated into environmental economics to explain behaviour and as an input into policy (Shogren and Taylor, 2008). Starmer (2000) provides a comprehensive review and highlights that more field-based data can help advance the debates. Similarly, Gollier et al. (2013) note that EUT is still most widely used to describe choice under risk, despite considerable evidence of violations from lab experiments. The question then is, does risk aversion consistently predict self-protection from air pollution in the field?

Due to the limited empirical evidence on this question, we can look to existing studies that map risk preferences onto choice in other contexts. No clear answers are available because the results are mixed. To illustrate, on the one hand, Anderson and Mellor (2008) found that higher seat belt usage, lower smoking and drinking is associated with higher risk aversion in a sample of students and adults from the USA. But on the other hand, Rustichini et al. (2016) found no association between risk aversion and the number of traffic accidents, credit scores or the body mass index in a sample of trainee truckers, also from the USA, but they found a significant association with smoking status. Three distinct but interconnected explanations emerge from the literature. Firstly, psychologists, and more recently economists point out that an individual's propensity to take risks varies across domains, i.e., an individual maybe risk-taking in the finance domain but not the health domain (Weber et al., 2002; Barseghyan et al., 2011). Secondly, the type of risk preferences measure and method, i.e., incentive-compatible lotteries using experimental methods or self-reported surveys using questionnaire methods, can influence observed empirical patterns partly because they capture risk-taking in specific behavioural contexts (Galizzi et al., 2016; Ioannou and Sadeh, 2016).[11] Thirdly, studies considering a narrow set of behaviours to represent decision-making in a domain are likely to present an incomplete picture because of the propensity of individuals to compensate across a range of actions within a domain as is evident from the previous discussion on behavioural spillovers. For example, an individual may not wear a seatbelt because she drives on safer, low-traffic routes.

To add to these debates, Paper 3 in Chapter 4 explores the links between risk aversion, and everyday air pollution avoidance and risk-taking using a lab-in-the-field experiment amongst a pool of urban cyclists. We know less about the everyday air pollution avoidance and risk-taking choices made by cyclists despite the fact that cycling is an important pro-environmental and health behaviour. There is also a concerted push to increase active travel in global cities to reduce individual emissions from transport and tackle diseases associated with sedentary lifestyles like obesity (Giles-Corti et al., 2016). The contributions of this paper are empirical and methodological, because it explores whether risk

[11]Galizzi et al. (2016) provides a comprehensive review on debates over the ability of different risk measures to predict behaviour.

preferences predict choices in two new behavioural domains amongst active travellers, i.e., air pollution avoidance and risk-taking while cycling, and tests a variety of risk preference measures against self-reported behaviours in the field.

Paper 4 in Chapter 5 takes a new slant on understanding air pollution avoidance, by considering whether persuasive social norms messaging can change avoidance behaviour. In doing so, it aims to augment existing literature by looking at how to promote avoidance using behavioural insights when individuals are outdoors. It also explores the psycho-social underpinnings of such choices by considering the role of social norms. Persuasive messaging that makes desirable social norms salient is widely considered a robust behavioural lever in diverse contexts including driving safety (Lawrence, 2015), energy, water and other conservation behaviours (Allcott, 2011; Ferraro and Price, 2013; Goldstein et al., 2008; Dolan and Metcalfe, 2015), and antibiotics over-prescription (Hallsworth et al., 2016). But it has failed to have impacts in other contexts like fees repayment (Silva and John, 2017) and decisions to inflate tires for fuel efficiency gains (Yeomans and Herberich, 2014) (relative to informational control conditions), and in replication studies using different populations (Bohner and Schlüter, 2014). Other research has remarked that treatment effects are heterogeneous, based on prior individual/household attributes: for example, Ferraro and Price (2013) found that appeals to social norms elicited the most considerable reductions in water use amongst among high-use households (also in Allcott (2011)). These mixed and heterogeneous treatment effects raise questions about whether and how informational interventions vary across contexts, and what factors can explain underlying variations. Moreover, whether social norms messaging can change air pollution avoidance behaviour is an open empirical question, as I am unaware of other studies which have explored this question. The chief contributions from this exploratory study are: to explore the additional benefits of using persuasive social norms messaging compared to a control condition with health-risk information in a new behavioural context and to underscore the role of prior beliefs as a driver of responses to social norms information.

To recap, Papers 3 and 4 augment the existing literature by exploring various psycho-social factors that could drive people's everyday choices to protect themselves from environmental risks like air pollution while cycling, which is an increasingly policy-relevant pro-environmental and health behaviour in urban contexts. In Paper 3, the data showed that air pollution risk perception - rather than risk aversion - was correlated with avoidance in this sample. The findings of Paper 4, suggest that prior beliefs about air quality seem to guide responses to social norm interventions, which in turn augment debates on which factors affect the efficacy of persuasive messaging to change behaviour across different contexts. The methodological approach, results, potential limitations, and way forward are discussed in Chapter 4 and 5 for Papers 3 and 4 respectively.

A.4.3 People's choices to cooperate and protect common pool resources: Paper 5

The management of shared natural resources is a continuing struggle: for example, around 90% of the world's fish stocks now fully or overfished and a 17% increase in production forecast by 2025, with unfortunate environmental, food and livelihood security implications (FAO, 2016). Such scenarios have usefully been characterised as social dilemmas, i.e., those interdependent situations where individuals face short-term incentives to maximise their self-interest leaving all those in society worse off. The pursuit of rational self-interest is predicted to result in the over-extraction from the shared resource in the case of an appropriation dilemma (e.g., in common pool resource (CPR) extraction games) or under-provide the shared resource in a provision dilemma (e.g., public goods games).[12]

However, contrary to the standard 'tragedy of the commons' model (Hardin, 1968), lab and field-based insights paint a more complex picture of behaviour in social dilemmas, because they reveal examples of both individuals acting pro-socially to cooperate and failing to do so (Ostrom et al., 2002). For example, a standard finding from experiments using linear voluntary contribution public goods game is that individuals contribute around 40-60% of their endowment versus the predicted zero level of investment at the Nash equilibrium in the first period, after which contributions typically tend to decline (Chaudhuri, 2011). Similarly, in non-linear appropriation CPR games, individuals show a pulsing pattern where seemed to increase their appropriation from the CPR until there was a substantial reduction in returns, at which time they tended to reduce their investments (Ostrom, 2006). Subsequent work has aimed to unpack the drivers of cooperation, by disentangling the effects of attributes of the resources systems and dynamics (e.g. system dynamics and replacement rate), governance systems (e.g. monitoring institutions, property rights, network structure), users (e.g. social norms and capital, types), and interactions between them (Ostrom, 2009).

A policy question in the face of this possible pro-sociality is whether governments should focus on strengthening local institutions which can support cooperation. Apart from the fact that many successful case studies of local management rely on decentralised

[12]Ostrom (2006) defines a common-pool resource as 'an irrigation system, a fishing ground, a forest, the Internet, or the stratosphere is a natural or man-made resource from which it is difficult to exclude or limit users once the resource is provided by nature or humans' (pp. 151).

local institutions (Ostrom et al., 2002), another concern is the worrying potential of top-down policy incentive-based interventions to 'crowd-out' pro-social preferences due to undermining moral sentiments or by changing the way obligations to preserve nature are perceived by agents, reducing cooperation in the long-run (Bowles, 2008; Gneezy et al., 2011). As noted by Noussair and van Soest (2014), communication and the use of peer-to-peer enforcement mechanisms like punishments and rewards have received maximum attention in the experimental literature. Communication, even if it is non-consequential for payoffs, have been found to improve cooperation particularly if it is face-to-face, possibly because it allows players to coordinate their actions and enhances understanding of the socially efficient strategy. Other studies similarly note that pro-sociality increases with public visibility in strategic situations (Bohnet and Frey, 1999).

However, the effects of peer monitoring and sanctioning on cooperation are far less robust. Peer monitoring which imposes some positive cost to the individual can be seen as another type of pro-social behaviour, as it confers an environmental benefit to society. Experimental evidence - most commonly from public goods experiments in the lab - show that peer sanctioning can increase cooperation especially over the long-run (Fehr and Gachter, 2000; Boyd et al., 2003; Gächter et al., 2008). However, there are also cases of anti-social punishment where cooperators are punished instead which can impede the evolution of cooperation (Herrmann et al., 2008; Rand et al., 2010). Other features which determine the effectiveness of peer monitoring include the institutional features modelled in the experimental design like the group composition, punishment cost and severity including the threat of expulsion, the opportunities for counter-punishment, and more recently the structure of the monitoring and punishment network which restricts the punishment opportunities available to agents (Nikiforakis, 2008; Cinyabuguma et al., 2005; Carpenter et al., 2012; Leibbrandt et al., 2015; Boosey and Isaac, 2016). For example, Leibbrandt et al. (2015) found that contributions to the public good are higher when more punishment opportunities are available, but that punishment is also higher. Boosey and Isaac (2016) observed that the network structure affects the incidence of anti-social punishment.

Somewhat surprisingly, there is less research on peer punishment in non-linear CPR appropriation dilemmas. The two main differences between linear voluntary public goods games and non-linear CPR appropriation games are (i) the returns from appropriation are non-linear to stimulate resource dynamics found in the field resulting in the increased complexity of the payoff space, and (ii) the subtractability of resource units implying that individuals can take from the shared resource endowment and reduce payoffs to others in the group (Ostrom et al., 1992). In this setting pro-sociality by some agents can be undone due to the selfish behaviour of others, making harvesting from the CPR 'strategic substitutes' (Noussair and van Soest, 2014). Existing research primarily investigates perfect peer sanctioning institutions, i.e., everyone can monitor and punish each other, and paints a more pessimistic picture because it has a weaker effect on appropriation resulting in outcomes closer to the Nash equilibrium (Cason and Gangadharan, 2015; Ostrom et al., 1992). This gap in the literature underlines the observation by Currarini et al. (2016) that our understanding of factors related to more complex resource characteristics and the role of network interactions in facilitating or hindering cooperation is relatively limited.

The effect of imperfect peer monitoring and punishment on cooperation is empirically unclear. Thus, Paper 5 contributes to the existing literature by exploring how the structure of imperfect monitoring and punishment networks affect appropriation and punishment in a non-linear CPR dilemma, by using a lab experiment. To the best of our knowledge, we are unaware of any other studies which elicit beliefs in either a non-linear CPR dilemma or alongside the monitoring and punishment network architecture, or applies network architectures to study imperfect peer monitoring institutions in a CPR dilemma.

Bibliography

Afif, Z. (2017). "nudge units" – where they came from and what they can do. http://blogs.worldbank.org/developmenttalk/nudge-units-where-they-came-and-what-they-can-do [accessed" April 2018].

Akerlof, G. A. and Shiller, R. J. (2015). *Phishing for phools: The economics of manipulation and deception*. Princeton University Press.

Allcott, H. (2011). Social norms and energy conservation. *Journal of public Economics*, 95(9-10):1082–1095.

Anderson, L. R. and Mellor, J. M. (2008). Predicting health behaviors with an experimental measure of risk preference. *Journal of health economics*, 27(5):1260–1274.

Arrow, K., Cropper, M., Gollier, C., Groom, B., Heal, G., Newell, R., Nordhaus, W., Pindyck, R., Pizer, W., Portney, P., et al. (2013). Determining benefits and costs for future generations. *Science*, 341(6144):349–350.

Arrow, K. J. (1969). The organization of economic activity: issues pertinent to the choice of market versus nonmarket allocation. *The analysis and evaluation of public expenditure: the PPB system*, 1:59–73.

Ashraf, N., Camerer, C. F., and Loewenstein, G. (2005). Adam smith, behavioral economist. *Journal of Economic Perspectives*, 19(3):131–145.

Atkinson, G., Bateman, I., and Mourato, S. (2012). Recent advances in the valuation of ecosystem services and biodiversity. *Oxford Review of Economic Policy*, 28(1):22–47.

Bamberg, S. and Möser, G. (2007). Twenty years after hines, hungerford, and tomera: A new meta-analysis of psycho-social determinants of pro-environmental behaviour. *Journal of environmental psychology*, 27(1):14–25.

Barrett, S. (1994). Self-enforcing international environmental agreements. *Oxford Economic Papers*, pages 878–894.

Barrett, S. and Dannenberg, A. (2012). Climate negotiations under scientific uncertainty. *Proceedings of the National Academy of Sciences*, 109(43):17372–17376.

Barseghyan, L., Prince, J., and Teitelbaum, J. C. (2011). Are risk preferences stable across contexts? evidence from insurance data. *American Economic Review*, 101(2):591–631.

Bartkowski, B., Lienhoop, N., and Hansjürgens, B. (2015). Capturing the complexity of biodiversity: A critical review of economic valuation studies of biological diversity. *Ecological economics*, 113:1–14.

Beshears, J., Choi, J. J., Laibson, D., and Madrian, B. C. (2008). How are preferences revealed? *Journal of public economics*, 92(8-9):1787–1794.

Bohner, G. and Schlüter, L. E. (2014). A room with a viewpoint revisited: Descriptive norms and hotel guests' towel reuse behavior. *PloS one*, 9(8):e104086.

Bohnet, I. and Frey, B. S. (1999). Social distance and other-regarding behavior in dictator games: Comment. *American Economic Review*, 89(1):335–339.

Boosey, L. and Isaac, R. M. (2016). Asymmetric network monitoring and punishment in public goods experiments. *Journal of Economic Behavior & Organization*, 132:26–41.

Boulding, K. (1966). The economics of the coming spaceship earth. inenvironmental quality in a growing economy. h. jarrett, ed: 3–14.

Bowles, S. (2008). Policies designed for self-interested citizens may undermine" the moral sentiments": Evidence from economic experiments. *science*, 320(5883):1605–1609.

Boyd, R., Gintis, H., Bowles, S., and Richerson, P. J. (2003). The evolution of altruistic punishment. *Proceedings of the National Academy of Sciences*, 100(6):3531–3535.

Carlsson, F. (2010). Design of stated preference surveys: Is there more to learn from behavioral economics? *Environmental and Resource Economics*, 46(2):167–177.

Carlsson, F. and Johansson-Stenman, O. (2012). Behavioral economics and environmental policy. *Annu. Rev. Resour. Econ.*, 4(1):75–99.

Carpenter, J., Kariv, S., and Schotter, A. (2012). Network architecture, cooperation and punishment in public good experiments. *Review of Economic Design*, 16(2-3):93–118.

Carraro, C., Marchiori, C., and Sgobbi, A. (2007). Negotiating on water: insights from non-cooperative bargaining theory. *Environment and Development Economics*, 12(2):329–349.

Carson, R. (2002). *Silent spring.* Houghton Mifflin Harcourt.

Carson, R. T. (2012). Contingent valuation: A practical alternative when prices aren't available. *Journal of Economic Perspectives*, 26(4):27–42.

Cason, T. N. and Gangadharan, L. (2015). Promoting cooperation in nonlinear social dilemmas through peer punishment. *Experimental Economics*, 18(1):66–88.

Ceballos, G., Ehrlich, P. R., Barnosky, A. D., García, A., Pringle, R. M., and Palmer, T. M. (2015). Accelerated modern human–induced species losses: Entering the sixth mass extinction. *Science advances*, 1(5):e1400253.

Chabris, C. F., Laibson, D. I., and Schuldt, J. P. (2010). Intertemporal choice. In *Behavioural and Experimental Economics*, pages 168–177. Springer.

Chaudhuri, A. (2011). Sustaining cooperation in laboratory public goods experiments: a selective survey of the literature. *Experimental Economics*, 14(1):47–83.

Cinyabuguma, M., Page, T., and Putterman, L. (2005). Cooperation under the threat of expulsion in a public goods experiment. *Journal of public Economics*, 89(8):1421–1435.

Clifford, A., Lang, L., Chen, R., Anstey, K. J., and Seaton, A. (2016). Exposure to air pollution and cognitive functioning across the life course–a systematic literature review. *Environmental research*, 147:383–398.

Coase, R. H. (1974). The lighthouse in economics. *The journal of law and economics*, 17(2):357–376.

Cropper, M. L. and Oates, W. E. (1992). Environmental economics: a survey. *Journal of economic literature*, 30(2):675–740.

Croson, R. and Treich, N. (2014). Behavioral environmental economics: promises and challenges. *Environmental and Resource Economics*, 58(3):335–351.

Currarini, S., Marchiori, C., and Tavoni, A. (2016). Network economics and the environment: insights and perspectives. *Environmental and Resource Economics*, 65(1):159–189.

Currie, J., Zivin, J. G., Mullins, J., and Neidell, M. (2014). What do we know about short-and long-term effects of early-life exposure to pollution? *Annu. Rev. Resour. Econ.*, 6(1):217–247.

Dales, J. (1968). Pollution, propertyy and prices. toronto: Univ.

Daly, H. E. (1973). *Toward a steady-state economy.* Freeman.

Dasgupta, P., Southerton, D., Ulph, A., and Ulph, D. (2016). Consumer behaviour with environmental and social externalities: implications for analysis and policy. *Environmental and Resource Economics*, 65(1):191–226.

Dasgupta, P. S. and Heal, G. M. (1979). *Economic theory and exhaustible resources.* Cambridge University Press.

DellaVigna, S. (2009). Psychology and economics: Evidence from the field. *Journal of Economic literature*, 47(2):315–72.

DellaVigna, S. and La Ferrara, E. (2015). Economic and social impacts of the media. In *Handbook of media economics*, volume 1, pages 723–768. Elsevier.

DellaVigna, S. and Malmendier, U. (2006). Paying not to go to the gym. *American Economic Review*, 96(3):694–719.

Diamond, P. A. and Hausman, J. A. (1994). Contingent valuation: is some number better than no number? *Journal of economic perspectives*, 8(4):45–64.

Dolan, P. and Galizzi, M. M. (2015). Like ripples on a pond: Behavioral spillovers and their implications for research and policy. *Journal of Economic Psychology*, 47:1–16.

Dolan, P., Hallsworth, M., Halpern, D., King, D., Metcalfe, R., and Vlaev, I. (2012). Influencing behaviour: The mindspace way. *Journal of Economic Psychology*, 33(1):264–277.

Dolan, P. and Laffan, K. (2016). Bad air days: The effects of air quality on different measures of subjective well-being. *Journal of Benefit-Cost Analysis*, 7(1):147–195.

Dolan, P. and Metcalfe, R. (2015). Neighbors, knowledge, and nuggets: two natural field experiments on the role of incentives on energy conservation. Technical report, Becker Friedman Institute for Research in Economics. Becker Friedman Institute for Research in Economics Working Paper No. 2589269.

Ebenstein, A., Lavy, V., and Roth, S. (2016). The long-run economic consequences of high-stakes examinations: evidence from transitory variation in pollution. *American Economic Journal: Applied Economics*, 8(4):36–65.

Egebark, J. and Ekström, M. (2016). Can indifference make the world greener? *Journal of Environmental Economics and Management*, 76:1–13.

Evans, J. S. B. (2008). Dual-processing accounts of reasoning, judgment, and social cognition. *Annu. Rev. Psychol.*, 59:255–278.

Evans, J. S. B. and Stanovich, K. E. (2013). Dual-process theories of higher cognition: Advancing the debate. *Perspectives on psychological science*, 8(3):223–241.

FAO (2016). The state of world fisheries and aquaculture. http://www.fao.org/3/a-i5555e.pdf [Access date: April 2017].

Fehr, E. and Gachter, S. (2000). Cooperation and punishment in public goods experiments. *American Economic Review*, 90(4):980–994.

Fehr, E. and Gächter, S. (2000). Fairness and retaliation: The economics of reciprocity. *Journal of economic perspectives*, 14(3):159–181.

Fehr, E. and Schmidt, K. M. (2006). The economics of fairness, reciprocity and altruism–experimental evidence and new theories. *Handbook of the economics of giving, altruism and reciprocity*, 1:615–691.

Ferraro, P. J. and Hanauer, M. M. (2014). Quantifying causal mechanisms to determine how protected areas affect poverty through changes in ecosystem services and infrastructure. *Proceedings of the National Academy of Sciences*, 111(11):4332–4337.

Ferraro, P. J. and Price, M. K. (2013). Using nonpecuniary strategies to influence behavior: evidence from a large-scale field experiment. *Review of Economics and Statistics*, 95(1):64–73.

Fischbacher, U., Gächter, S., and Fehr, E. (2001). Are people conditionally cooperative? evidence from a public goods experiment. *Economics letters*, 71(3):397–404.

Friedman, M. and Savage, L. J. (1948). The utility analysis of choices involving risk. *Journal of political Economy*, 56(4):279–304.

Gächter, S., Renner, E., and Sefton, M. (2008). The long-run benefits of punishment. *Science*, 322(5907):1510–1510.

Galizzi, M. M., Miraldo, M., and Stavropoulou, C. (2016). In sickness but not in wealth: Field evidence on patients' risk preferences in financial and health domains. *Medical Decision Making*, 36(4):503–517.

Gigerenzer, G. and Gaissmaier, W. (2011). Heuristic decision making. *Annual review of psychology*, 62:451–482.

Giles-Corti, B., Vernez-Moudon, A., Reis, R., Turrell, G., Dannenberg, A. L., Badland, H., Foster, S., Lowe, M., Sallis, J. F., Stevenson, M., et al. (2016). City planning and population health: a global challenge. *The lancet*, 388(10062):2912–2924.

Glimcher, P. W. and Rustichini, A. (2004). Neuroeconomics: the consilience of brain and decision. *Science*, 306(5695):447–452.

Gneezy, U., Meier, S., and Rey-Biel, P. (2011). When and why incentives (don't) work to modify behavior. *Journal of Economic Perspectives*, 25(4):191–210.

Goldstein, N. J., Cialdini, R. B., and Griskevicius, V. (2008). A room with a viewpoint: Using social norms to motivate environmental conservation in hotels. *Journal of consumer Research*, 35(3):472–482.

Gollier, C., Hammitt, J. K., and Treich, N. (2013). Risk and choice: A research saga. *Journal of risk and uncertainty*, 47(2):129–145.

Gordon, H. S. (1954). The economic theory of a common-property resource: the fishery. In *Classic Papers in Natural Resource Economics*, pages 178–203. Springer.

Gowdy, J. M. (2008). Behavioral economics and climate change policy. *Journal of Economic Behavior & Organization*, 68(3-4):632–644.

Groom, B., Hepburn, C., Koundouri, P., and Pearce, D. (2005). Declining discount rates: the long and the short of it. *Environmental and resource economics*, 32(4):445–493.

Hahn, R. W. and Stavins, R. N. (1992). Economic incentives for environmental protection: integrating theory and practice. *The American Economic Review*, 82(2):464–468.

Hallsworth, M., Chadborn, T., Sallis, A., Sanders, M., Berry, D., Greaves, F., Clements, L., and Davies, S. C. (2016). Provision of social norm feedback to high prescribers of antibiotics in general practice: a pragmatic national randomised controlled trial. *The Lancet*, 387(10029):1743–1752.

Hammitt, J. K. (2013). Positive versus normative justifications for benefit-cost analysis: Implications for interpretation and policy. *Review of Environmental Economics and Policy*, 7(2):199–218.

Hardin, G. (1968). The tragedy of the commons. *Science*, 162(3859):1243–1248.

Hausman, J. (2012). Contingent valuation: from dubious to hopeless. *Journal of Economic Perspectives*, 26(4):43–56.

Heal, G. (2007). A celebration of environmental and resource economics. *Review of Environmental Economics and Policy*, 1(1):7–25.

Heal, G. and Millner, A. (2014). Reflections: Uncertainty and decision making in climate change economics. *Review of Environmental Economics and Policy*, 8(1):120–137.

Helm, D. and Hepburn, C. (2012). The economic analysis of biodiversity: an assessment. *Oxford Review of Economic Policy*, 28(1):1–21.

Henrich, J., Boyd, R., Bowles, S., Camerer, C., Fehr, E., Gintis, H., and McElreath, R. (2001). In search of homo economicus: behavioral experiments in 15 small-scale societies. *American Economic Review*, 91(2):73–78.

Hepburn, C., Duncan, S., and Papachristodoulou, A. (2010). Behavioural economics, hyperbolic discounting and environmental policy. *Environmental and Resource Economics*, 46(2):189–206.

Herrmann, B., Thöni, C., and Gächter, S. (2008). Antisocial punishment across societies. *Science*, 319(5868):1362–1367.

Hicks, J. R. (1939). The foundations of welfare economics. *The Economic Journal*, 49(196):696–712.

Hotelling, H. (1931). The economics of exhaustible resources. *Journal of political Economy*, 39(2):137–175.

Howell, R. A. (2011). Lights, camera... action? altered attitudes and behaviour in response to the climate change film the age of stupid. *Global Environmental Change*, 21(1):177–187.

Howell, R. A. (2014). Investigating the long-term impacts of climate change communications on individuals' attitudes and behavior. *Environment and Behavior*, 46(1):70–101.

Ioannou, C. A. and Sadeh, J. (2016). Time preferences and risk aversion: Tests on domain differences. *Journal of Risk and Uncertainty*, 53(1):29–54.

Jacobsen, G. D. (2011). The al gore effect: an inconvenient truth and voluntary carbon offsets. *Journal of Environmental Economics and Management*, 61(1):67–78.

Janke, K. (2014). Air pollution, avoidance behaviour and children's respiratory health: Evidence from england. *Journal of health economics*, 38:23–42.

Janssen, M. A., Holahan, R., Lee, A., and Ostrom, E. (2010). Lab experiments for the study of social-ecological systems. *Science*, 328(5978):613–617.

Kahneman, D. (2011). *Thinking, fast and slow.* Macmillan.

Kahneman, D. and Knetsch, J. L. (1992). Valuing public goods: the purchase of moral satisfaction. *Journal of environmental economics and management*, 22(1):57–70.

Kahneman, D., Knetsch, J. L., and Thaler, R. H. (1990). Experimental tests of the endowment effect and the coase theorem. *Journal of political Economy*, 98(6):1325–1348.

Kahneman, D., Knetsch, J. L., and Thaler, R. H. (1991). Anomalies: The endowment effect, loss aversion, and status quo bias. *Journal of Economic perspectives*, 5(1):193–206.

Kahneman, D., Ritov, I., Jacowitz, K. E., and Grant, P. (1993). Stated willingness to pay for public goods: A psychological perspective. *Psychological science*, 4(5):310–315.

Kahneman, D., Slovic, P., and Tversky, A. (1982). Judgments under uncertainty. *Heuristics and Biases, Cambridge*.

Kahneman, D. and Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2):263–292.

Kaldor, N. (1939). Welfare propositions of economics and interpersonal comparisons of utility. *The Economic Journal*, pages 549–552.

Karlan, D. and McConnell, M. A. (2014). Hey look at me: The effect of giving circles on giving. *Journal of Economic Behavior & Organization*, 106:402–412.

Kaul, I., Grungberg, I., and Stern, M. A. (1999). Global public goods. *Global public goods*, 450.

Kling, C. L., Phaneuf, D. J., and Zhao, J. (2012). From exxon to bp: Has some number become better than no number? *Journal of Economic Perspectives*, 26(4):3–26.

Knetsch, J. L. and Sinden, J. A. (1984). Willingness to pay and compensation demanded: Experimental evidence of an unexpected disparity in measures of value. *The Quarterly Journal of Economics*, 99(3):507–521.

Kollmuss, A. and Agyeman, J. (2002). Mind the gap: why do people act environmentally and what are the barriers to pro-environmental behavior? *Environmental education research*, 8(3):239–260.

Kolstad, C. et al. (2011). Intermediate environmental economics: International edition. *OUP Catalogue*.

Laibson, D. (1997). Golden eggs and hyperbolic discounting. *The Quarterly Journal of Economics*, 112(2):443–478.

Laville, S. (2017). https://www.theguardian.com/environment/2017/apr/22/nearly-40-million-people-live-in-uk-areas-with-illegal-air-pollution [Accessed date: 23 March 2018].

Lawrence, N. K. (2015). Highlighting the injunctive norm to reduce phone-related distracted driving. *Social Influence*, 10(2):109–118.

Leibbrandt, A., Ramalingam, A., Sääksvuori, L., and Walker, J. M. (2015). Incomplete punishment networks in public goods games: experimental evidence. *Experimental Economics*, 18(1):15–37.

List, J. A. (2003). Does market experience eliminate market anomalies? *The Quarterly Journal of Economics*, 118(1):41–71.

List, J. A. (2004). Neoclassical theory versus prospect theory: Evidence from the marketplace. *Econometrica*, 72(2):615–625.

List, J. A. and Millimet, D. L. (2008). The market: Catalyst for rationality and filter of irrationality. *The BE Journal of Economic Analysis & Policy*, 8(1).

List, J. A. and Price, M. K. (2016). The use of field experiments in environmental and resource economics. *Review of Environmental Economics and Policy*, 10(2):206–225.

Margetts, E. A. and Kashima, Y. (2017). Spillover between pro-environmental behaviours: The role of resources and perceived similarity. *Journal of Environmental Psychology*, 49:30–42.

McCabe, K., Houser, D., Ryan, L., Smith, V., and Trouard, T. (2001). A functional imaging study of cooperation in two-person reciprocal exchange. *Proceedings of the National Academy of Sciences*, 98(20):11832–11835.

McClure, S. M., Laibson, D. I., Loewenstein, G., and Cohen, J. D. (2004). Separate neural systems value immediate and delayed monetary rewards. *Science*, 306(5695):503–507.

Metrick, A. and Weitzman, M. L. (1998). Conflicts and choices in biodiversity preservation. *Journal of Economic Perspectives*, 12(3):21–34.

Mullainathan, S. and Thaler, R. H. (2000). Behavioral economics. Technical Report 7948, National Bureau of Economic Research.

Nikiforakis, N. (2008). Punishment and counter-punishment in public good games: Can we really govern ourselves? *Journal of Public Economics*, 92(1-2):91–112.

Noussair, C. N. and van Soest, D. P. (2014). Economic experiments and environmental policy. *Annu. Rev. Resour. Econ.*, 6(1):319–337.

Nunes, P. A. and van den Bergh, J. C. (2001). Economic valuation of biodiversity: sense or nonsense? *Ecological economics*, 39(2):203–222.

Nyborg, K., Howarth, R. B., and Brekke, K. A. (2006). Green consumers and public policy: On socially contingent moral motivation. *Resource and energy economics*, 28(4):351–366.

Ostrom, E. (1998). A behavioral approach to the rational choice theory of collective action: Presidential address, american political science association, 1997. *American political science review*, 92(1):1–22.

Ostrom, E. (2000). Collective action and the evolution of social norms. *Journal of economic perspectives*, 14(3):137–158.

Ostrom, E. (2006). The value-added of laboratory experiments for the study of institutions and common-pool resources. *Journal of Economic Behavior & Organization*, 61(2):149–163.

Ostrom, E. (2009). A general framework for analyzing sustainability of social-ecological systems. *Science*, 325(5939):419–422.

Ostrom, E., Walker, J., and Gardner, R. (1992). Covenants with and without a sword: Self-governance is possible. *American political science Review*, 86(2):404–417.

Ostrom, E. E., Dietz, T. E., Dolšak, N. E., Stern, P. C., Stonich, S. E., and Weber, E. U. (2002). *The drama of the commons.* National Academy Press.

Palmer, C. and Di Falco, S. (2012). Biodiversity, poverty, and development. *Oxford Review of Economic Policy*, 28(1):48–68.

Pearce, D. (2002). An intellectual history of environmental economics. *Annual review of energy and the environment*, 27(1):57–81.

Pearce, D., Groom, B., Hepburn, C., Koundouri, P., et al. (2003). Valuing the future. *World economics*, 4(2):121–141.

Perman, R., Yue, M., James, M., and Michael, C. (2003). Natural resource and environmental economics.

Pigou, A. (1920). *The economics of welfare*. Routledge.

Polasky, S., Johnson, K., Keeler, B., Kovacs, K., Nelson, E., Pennington, D., Plantinga, A. J., and Withey, J. (2012). Are investments to promote biodiversity conservation and ecosystem services aligned? *Oxford Review of Economic Policy*, 28(1):139–163.

Pope III, C. A., Ezzati, M., and Dockery, D. W. (2009). Fine-particulate air pollution and life expectancy in the united states. *New England Journal of Medicine*, 360(4):376–386.

Rand, D. G., Armao IV, J. J., Nakamaru, M., and Ohtsuki, H. (2010). Anti-social punishment can prevent the co-evolution of punishment and cooperation. *Journal of theoretical biology*, 265(4):624–632.

Rangel, A., Camerer, C., and Montague, P. R. (2008). A framework for studying the neurobiology of value-based decision making. *Nature reviews neuroscience*, 9(7):545.

Richter, A., van Soest, D., and Grasman, J. (2013). Contagious cooperation, temptation, and ecosystem collapse. *Journal of Environmental Economics and Management*, 66(1):141–158.

Røpke, I. (2004). The early history of modern ecological economics. *Ecological economics*, 50(3-4):293–314.

Røpke, I. (2005). Trends in the development of ecological economics from the late 1980s to the early 2000s. *Ecological economics*, 55(2):262–290.

Ross, L. and Nisbett, R. E. (2011). *The person and the situation: Perspectives of social psychology*. Pinter & Martin Publishers.

Rustagi, D., Engel, S., and Kosfeld, M. (2010). Conditional cooperation and costly monitoring explain success in forest commons management. *science*, 330(6006):961–965.

Rustichini, A., DeYoung, C. G., Anderson, J. E., and Burks, S. V. (2016). Toward the integration of personality theory and decision theory in explaining economic behavior: An experimental investigation. *Journal of Behavioral and Experimental Economics*, 64:122–137.

Rustichini, A., Dickhaut, J., Ghirardato, P., Smith, K., and Pardo, J. V. (2005). A brain imaging study of the choice procedure. *Games and Economic behavior*, 52(2):257–282.

Saberian, S., Heyes, A., and Rivers, N. (2017). Alerts work! air quality warnings and cycling. *Resource and Energy Economics*, 49:165–185.

Sager, L. (2016). Estimating the effect of air pollution on road safety using atmospheric temperature inversions. *Grantham Research Institute on Climate Change and the Environment working paper*, 251.

Sanfey, A. G., Rilling, J. K., Aronson, J. A., Nystrom, L. E., and Cohen, J. D. (2003). The neural basis of economic decision-making in the ultimatum game. *Science*, 300(5626):1755–1758.

Schubert, C. (2017). Green nudges: Do they work? are they ethical? *Ecological Economics*, 132:329–342.

Sethi, R. and Somanathan, E. (1996). The evolution of social norms in common property resource use. *The American Economic Review*, pages 766–788.

Shogren, J. F., Parkhurst, G. M., and Banerjee, P. (2010). Two cheers and a qualm for behavioral environmental economics. *Environmental and Resource Economics*, 46(2):235–247.

Shogren, J. F. and Taylor, L. O. (2008). On behavioral-environmental economics. *Review of Environmental Economics and Policy*, 2(1):26–44.

Silva, A. and John, P. (2017). Social norms don't always work: An experiment to encourage more efficient fees collection for students. *PloS one*, 12(5):e0177354.

Simon, H. A. (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics*, 69(1):99–118.

Slovic, P. (1987). Perception of risk. *Science*, 236(4799):280–285.

Smith, V. L. (1989). Theory, experiment and economics. *Journal of Economic Perspectives*, 3(1):151–169.

Spash, C. L. (2012). New foundations for ecological economics. *Ecological Economics*, 77:36–47.

Starmer, C. (2000). Developments in non-expected utility theory: The hunt for a descriptive theory of choice under risk. *Journal of economic literature*, 38(2):332–382.

Stavins, R. N. (2003). Experience with market-based environmental policy instruments. In *Handbook of environmental economics*, volume 1, pages 355–435. Elsevier.

Steg, L., Bolderdijk, J. W., Keizer, K., and Perlaviciute, G. (2014). An integrated framework for encouraging pro-environmental behaviour: The role of values, situational factors and goals. *Journal of Environmental Psychology*, 38:104–115.

Stern, N. (2008). The economics of climate change. *American Economic Review*, 98(2):1–37.

Sunstein, C. R. (2015). Nudges, agency, and abstraction: A reply to critics. *Review of Philosophy and Psychology*, 6(3):511–529.

Sunstein, C. R. and Reisch, L. A. (2018). Greener by default. Technical report, SSRN. Forthcoming Trinity Law Review.

Szyszkowicz, M., Willey, J. B., Grafstein, E., Rowe, B. H., and Colman, I. (2010). Air pollution and emergency department visits for suicide attempts in vancouver, canada. *Environmental health insights*, 4:EHI–S5662.

Tavoni, A., Dannenberg, A., Kallis, G., and Löschel, A. (2011). Inequality, communication, and the avoidance of disastrous climate change in a public goods game. *Proceedings of the National Academy of Sciences*, 108(29):11825–11829.

Thaler, R. (1980). Toward a positive theory of consumer choice. *Journal of Economic Behavior & Organization*, 1(1):39–60.

Thaler, R. and Sunstein, C. (2008). *Nudge: Improving decisions about health, wealth, and happiness.* Yale University Press.

Thaler, R. H. (2000). From homo economicus to homo sapiens. *Journal of economic perspectives*, 14(1):133–141.

Thaler, R. H. (2016). Behavioral economics: Past, present, and future. *American Economic Review*, 106(7):1577–1600.

Truelove, H. B., Carrico, A. R., Weber, E. U., Raimi, K. T., and Vandenbergh, M. P. (2014). Positive and negative spillover of pro-environmental behavior: An integrative review and theoretical framework. *Global Environmental Change*, 29:127–138.

Tversky, A. and Kahneman, D. (1986). Rational choice and the framing of decisions. *Journal of business*, pages S251–S278.

Tversky, A. and Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and uncertainty*, 5(4):297–323.

Venkatachalam, L. (2008). Behavioral economics for environmental policy. *Ecological Economics*, 67(4):640–645.

Weber, E. U., Blais, A.-R., and Betz, N. E. (2002). A domain-specific risk-attitude scale: Measuring risk perceptions and risk behaviors. *Journal of behavioral decision making*, 15(4):263–290.

Whitmarsh, L. and O'Neill, S. (2010). Green identity, green living? the role of pro-environmental self-identity in determining consistency across diverse pro-environmental behaviours. *Journal of Environmental Psychology*, 30(3):305–314.

Yeomans, M. and Herberich, D. (2014). An experimental test of the effect of negative social norms on energy-efficient investments. *Journal of Economic Behavior & Organization*, 108:187–197.

Zivin, J. G. and Neidell, M. (2009). Days of haze: Environmental information disclosure and intertemporal avoidance behavior. *Journal of Environmental Economics and Management*, 58(2):119–128.

Zivin, J. G. and Neidell, M. (2013). Environment, health, and human capital. *Journal of Economic Literature*, 51(3):689–730.

Appendix B

Data Appendix for Chapter 2

B.1 Estimation strategy: Cragg-Hurdle model

We assume that all subjects are faced with a two-step decision problem i.e. the first step is to decide whether to make a positive contribution, and the second step is then the decision of how much to give, conditional on the willingness to give at all. This can be estimated using a Cragg-Hurdle model, which treats the boundary value of £0 donations as a variable of analytical interest (Cragg 1971, Woolridge 2010). We can conceptualize donations as $y_i = d_i * h_i$, where y_i is the quasi-continuous observed value of the dependent variable, which are the donations made by subjects. The selection variable is d_i and takes the value of 1 if subjects choose a positive donation amount (given the set of explanatory variables) and 0 otherwise (which act as a lower limit that binds the dependent variable). Thus;

$$d_i = \begin{Bmatrix} 0 : c_i\gamma + r_i\delta + x_i\beta + \epsilon_i > 0 \\ 1 : otherwise, \end{Bmatrix} \tag{B.1}$$

From (B.1), c_i and r_i are the treatment dummies for species-habitat and cause-pubic recognition treatment groups, and γ and δ are their coefficients respectively. x_i and $beta$ are the vector of other explanatory variables and their coefficients, and ϵ_i is the associated standard normal error term. Once the subject has decided to donate, the second step of the decision problem is;

$$h_i^* = c_i\alpha + r_i\theta + x_i\rho + \upsilon_i \tag{B.2}$$

From (B.2), is the quasi-continuous latent dependent variable which is observed when $d_i = 1$. The explanatory variables remain the same i.e. c_i and r_i are the treatment dummies for species-habitat and Cause-Pubic Recognition treatment groups, x_i is the vector of other explanatory variables. α and θ are the coefficients on the treatment dummies and is the vector of coefficients on the explanatory variables, and is the error term. Importantly the parameters of the treatment dummies in for both the selection and latent dependent variables (i.e., d_i and h_i^*) may differ. This allows us to account for the fact that the decision to give may be influenced by different factors than the decision on the amount to give. The analysis was carried out in Stata using the *churdle* command in conjunction with the *margins* command to estimate the average marginal effect.

References:

Cragg, J. G. (1971). Some statistical models for limited dependent variables with application to the demand for durable goods. *Econometrica: Journal of the Econometric Society*, pages 829–844.

Wooldridge, J. M. (2010). Econometric analysis of cross section and panel data. MIT press.

B.2 Additional tables and figures

Figure B.1: Distribution of donation for all observations (N=377)

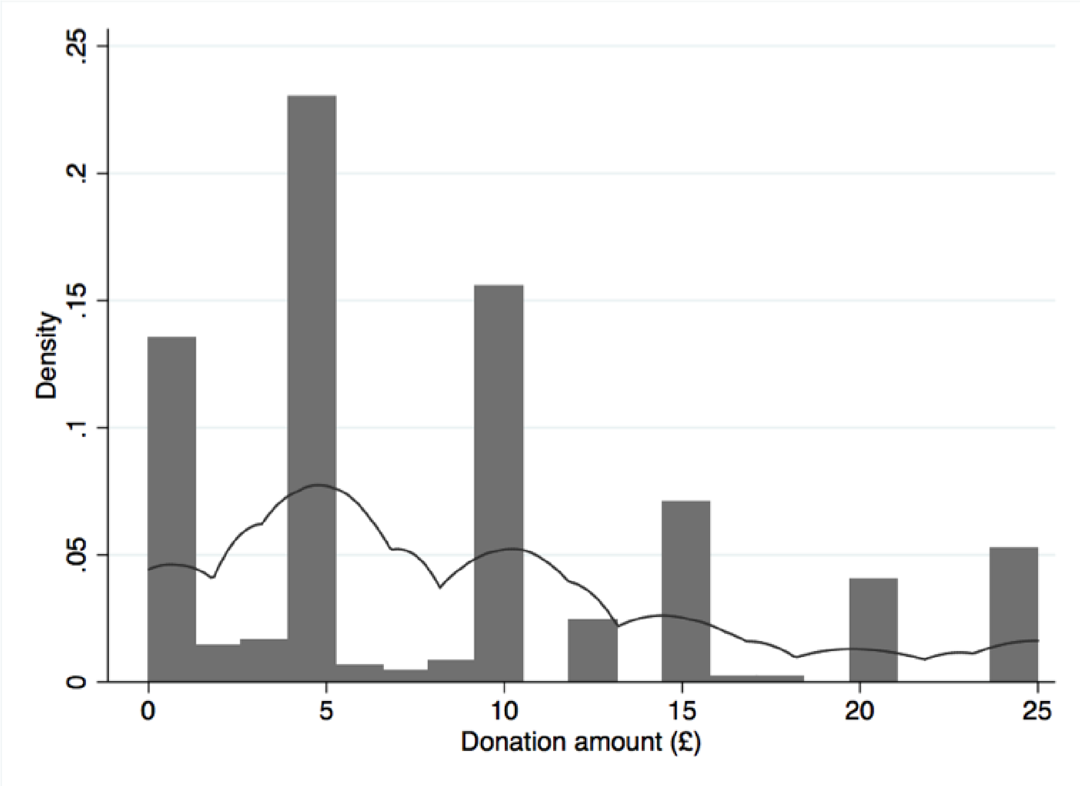


Table B.1: Description of variables

Variables	Description	N	Observed values			
			Mean	Std. Dev.	Min	Max
Study 1.- Donations						
Donations	Charitable donation decision from £0 to £25	377	8.51	6.99	0	25
Study 2.- Affect						
Happy	Self-report from PANAS-X affect schedule (Very slightly or none at all (0) to Extremely (4))	177	0.39	0.66	0	2
Angry	Self-report from PANAS-X affect schedule (Very slightly or none at all (0) to Extremely (4))	177	1.11	1.18	0	4
Sad	Self-report from PANAS-X affect schedule (Very slightly or none at all (0) to Extremely (4))	177	1.86	1.22	0	4
Guilty	Self-report from PANAS-X affect schedule (Very slightly or none at all (0) to Extremely (4))	177	0.78	0.96	0	4
Sympathy	Self-report from PANAS-X affect schedule (Very slightly or none at all (0) to Extremely (4))	177	2.13	1.19	0	4
Calm	Self-report from PANAS-X affect schedule (Very slightly or none at all (0) to Extremely (4))	177	2.03	1.13	0	4
Interest	Self-report from PANAS-X affect schedule (Very slightly or none at all (0) to Extremely (4))	177	2.08	1.12	0	4
Study 1 and 2: Pooled sample						
Donor	Previously made donations to charity (No (0), Yes (1))	554	0.76	0.43	0	1
Pro-environmental behaviour (PEB)	Average PEB score (Minimum (0) to Maximum (4))	554	2.28	1.02	0	4
Age	Continuous, in years	554	24.41	7.51	17	66
Gender	Categorical, Male (0), Female (1)	554	0.66	0.47	0	1
Job status	Categorical, Full time student (FTS, 0), Working full time (WFT, 1), Working part time (WPT, 2), Other (3)	554	0.36	0.86	0	3
Subjects/session	Number of subjects per session	554	16.11	3.77	1	20

Notes: The experiment was held during 16 November to 8 December 2016. The number of subjects per session ranged from 5 to 20 (maximum capacity).

Table B.2: Pre-treatment behaviour and socio-demographic characteristics by treatment group: Mean and standard deviation (S.D.)

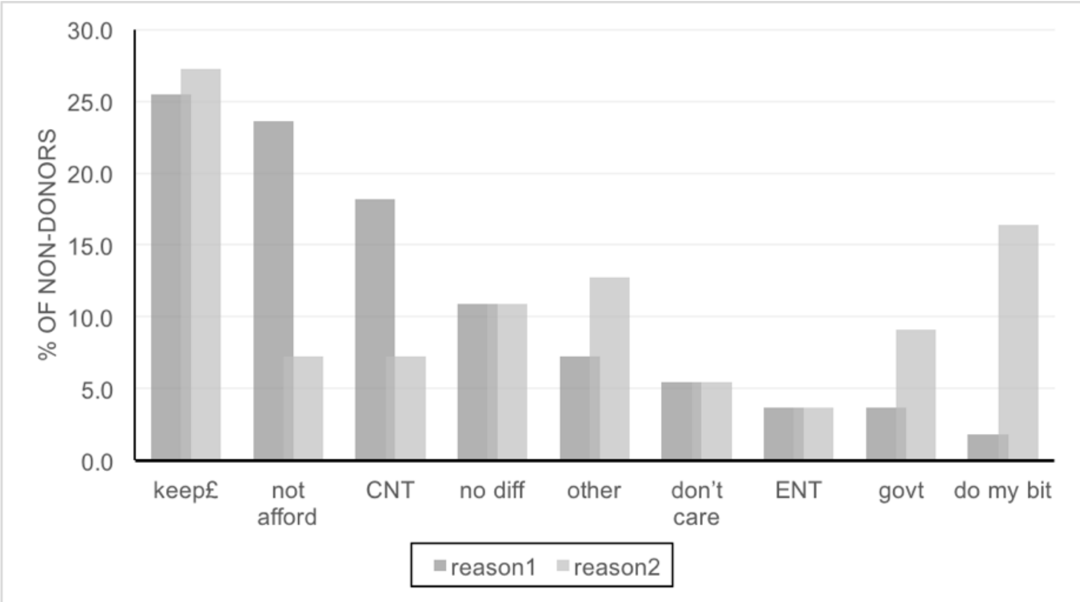
Treatment groups	Donors		PEB		Age		Gender		Job		N
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	
Study 1: Donations											
Bats Control videos	0.9	0.3	1.95	0.68	26.98	8.41	0.65	0.48	0.35	0.74	40
Bats Cause videos	0.78	0.42	1.78	0.78	22.76	4.94	0.66	0.48	0.15	0.53	41
Bats Cause videos + Public recognition	0.78	0.42	1.77	0.7	24.25	5.33	0.8	0.41	0.18	0.55	40
Lions Control videos	0.71	0.46	1.7	0.74	24	7.21	0.69	0.47	0.62	1.13	45
Lions Cause videos	0.67	0.47	1.72	0.81	23.89	7.78	0.52	0.51	0.33	0.9	46
Lions Cause videos + Public recognition	0.78	0.42	1.94	0.74	26.56	10.31	0.78	0.42	0.32	0.69	41
Savanna Control videos	0.8	0.41	1.83	0.76	23.68	5.75	0.66	0.48	0.39	0.92	44
Savanna Cause videos	0.76	0.43	1.67	0.68	23.88	8.55	0.64	0.48	0.29	0.81	42
Savanna Cause videos + Public recognition	0.74	0.45	1.7	0.72	24.03	6.31	0.53	0.51	0.34	0.94	38
Study 2: Affect											
Bats Control videos	0.74	0.44	2.03	0.62	24.19	8.26	0.74	0.44	0.45	0.85	31
Bats Cause videos	0.79	0.42	1.95	0.69	26.25	11.81	0.64	0.49	0.57	1.07	28
Lions Control videos	0.71	0.46	1.86	0.7	25.04	8.54	0.61	0.5	0.64	1.19	28
Lions Cause videos	0.77	0.43	1.88	0.69	22.47	3.71	0.77	0.43	0.13	0.57	30
Savanna Control videos	0.73	0.45	1.76	0.77	24.1	6.57	0.63	0.49	0.47	1.04	30
Savanna Cause videos	0.8	0.41	1.94	0.67	24.43	5.56	0.63	0.49	0.37	0.67	30
All	0.76	0.43	1.82	0.72	24.41	7.51	0.66	0.47	0.36	0.86	554

Table B.3: Donation with covariates: Study 1

Sample	All			Past Donors	
Estimation method	Tobit	CH, Probability	CH, Amount	CH, Probability	CH, Amount
Models	(1)	(2)	(3)	(4)	(5)
Species = 1, Lions	1.903**	0.428**	1.465	0.425*	1.506
	(0.87)	(0.21)	(1.37)	(0.25)	(1.47)
Species = 2, Savanna	0.6	-0.102	0.66	-0.044	1.14
	(0.92)	(0.19)	(1.46)	(0.23)	(1.53)
Cause = 1, Human	1.970**	0.165	2.953**	0.17	4.999***
	(0.93)	(0.21)	(1.39)	(0.24)	(1.41)
Cause = 2, Human + Recognition	0.208	-0.085	1.084	0.111	3.822**
	(0.92)	(0.21)	(1.49)	(0.24)	(1.58)
Past donor = 1, Yes	-0.847	0.03	-1.31		
	(0.95)	(0.20)	(1.41)		
Pro-environmental behaviour	1.380***	0.164	1.529**	0.141	2.581***
	(0.51)	(0.13)	(0.75)	(0.15)	(0.76)
Age	0.028	-0.006	0.074	-0.012	0.104
	(0.06)	(0.01)	(0.09)	(0.02)	(0.11)
Gender = 1, Female	1.219	0.278	1.109	0.366	0.779
	(0.86)	(0.19)	(1.40)	(0.23)	(1.50)
Job status = 1, WFT	-3.113**	-0.303	-5.731**	-0.151	-5.637**
	(1.37)	(0.33)	(2.62)	(0.37)	(2.61)
Job status = 2, WPT	-3.26	4.329***	-7.539	4.249***	-10.475**
	(2.27)	(0.47)	(4.69)	(0.40)	(5.21)
Job status = 3, Other	-2.822*	-0.14	-4.629*	-0.373	-5.679**
	(1.53)	(0.37)	(2.56)	(0.43)	(2.87)
Constant	12.78	0.658	14.377	0.946	-2.988
	(14.87)	(3.41)	(21.88)	(4.05)	(24.91)
Observations	377	377	377	289	289
Session controls	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable: donations (£0-25), all models use robust standard errors, with *** p¡0.01, ** p¡0.05, * p¡0.1. The Cragg-hurdle model (CH) treats the hurdle (£0 donations) as probit (Probability, models 1 and 3) and the amount (£1-25) spent as a truncated linear regression (Amount, models 2 and 4). For a one unit change in the predictor, the probit regression coefficients give the change in the z-score or probit index, and the truncated regression coefficients give the predicted change in the dependent variable. The omitted groups are Bats treatment group (control video without anthropogenic cause of endangerment and public recognition), Gender = 0-Male, Job = 0-Full time student (FTS; WFT: Working full time, WPT: Working part time).

Figure B.2: Reasons for not donating: Share of responses



Notes: Subjects could select their top two reasons for choosing to not donate from the drop down list of options which included (in a randomized order): (a) Rather keep the money (keep£) (b) I can't afford to (c) I don't trust the charity (CNT) (d) I don't believe that my donation will make a difference (no diff) (e) Other reason (other) (f) I already do my bit to help the planet (do my bit) (g) I don't trust this experiment (ENT) (h) The government should ensure that wildlife and their habitats are protected (govt).

Table B.4: Affect with covariates: Study 2

Ordinal logistic regressions Models	Angry (1)	Sad (2)	Guilty (3)	Sympathy (4)	Happy (5)	Calm (6)	Interest (7)
Species = 1, Lions	0.347	-0.138	0.265	0.309	0.941**	0.471	0.47
	(0.40)	(0.38)	(0.39)	(0.38)	(0.44)	(0.39)	(0.38)
Species = 2, Savanna	0.498	0.464	0.709*	0.483	0.549	0.625*	0.791**
	(0.36)	(0.33)	(0.40)	(0.35)	(0.42)	(0.37)	(0.38)
Cause = 1, Human	1.050***	0.610**	0.433	0.656**	0.756*	-0.005	0.833***
	(0.33)	(0.29)	(0.31)	(0.31)	(0.40)	(0.30)	(0.31)
Past donor = 1, Yes	0.458	-0.308	0.284	-0.077	0.654	-0.517	-0.012
	(0.39)	(0.36)	(0.42)	(0.37)	(0.50)	(0.35)	(0.37)
Pro-environmental behaviour	0.496**	0.542**	0.291	0.402	0.193	-0.178	0.525**
	(0.25)	(0.23)	(0.25)	(0.26)	(0.25)	(0.21)	(0.23)
Age	-0.018	-0.003	-0.027	-0.03	0.003	0.025	0.054**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Gender = 1, Female	0.461	0.257	0.555	0.16	-0.612	-0.407	0.097
	(0.31)	(0.33)	(0.37)	(0.30)	(0.39)	(0.34)	(0.32)
Job status = 1, WFT	-0.556	-0.868*	-0.189	-0.052	1.216**	0.428	0.177
	(0.75)	(0.51)	(0.53)	(0.71)	(0.58)	(0.77)	(0.75)
Job status = 2, WPT	-0.387	-1.072	-0.133	0.15	-0.41	0.525	-1.979**
	(0.72)	(0.97)	(0.74)	(0.90)	(0.92)	(1.06)	(0.84)
Job status = 3, Other	0.154	-0.972	-0.402	0.606	-0.207	1.407***	0.99
	(0.84)	(0.78)	(0.73)	(0.65)	(0.68)	(0.44)	(0.70)
Session dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	177	177	177	177	177	177	177

Notes: Dependent variable: self-reported affect (None at all (0) to Extremely (4)); all models use robust standard errors, with *** p¡0.01, ** p¡0.05, * p¡0.1. The ordinal logistical regression coefficients give the ordered log-odds. The omitted groups are Bats treatment group (B-D i.e., control video without anthropogenic cause of endangerment and public recognition), Gender = 0-Male, Job = 0-Full time student (FTS; WFT: Working full time, WPT: Working part time).

Table B.5: Implicit word associations

Type of word	Bats-Control video	Bats- Cause video	Lions-Control video	Lions-Cause video	Savanna-Control video	Savanna-Cause video	All
Negative Affect	23.66	12.64	16.67	13.98	10	6.45	13.9
Positive Affect	7.53	3.45	9.52	15.05	2.22	0	6.3
Other Affect	7.53	4.6	5.95	2.15	1.11	1.08	3.74
Ecological-related	24.73	34.48	39.29	37.63	35.56	39.78	35.25
Conservation-related	10.75	6.9	8.33	1.08	8.89	4.3	6.71
Destruction-related	12.9	20.69	8.33	21.51	16.67	24.73	17.47
Other	12.9	17.24	11.9	8.6	25.56	23.66	16.64
All categories	87.1	82.76	88.1	91.4	74.44	76.34	83.36

Notes: The five categories of words that emerged from the word association test are positive and negative affect, and words related to ecology (e.g. ecosystem, animal, lion, bats), conservation (e.g. protect, preserve, help) and destruction (e.g. hunting, endangerment, destruction). Affect-based words (positive, negative and other) are classified by the PANAS-X affect schedule (Watson and Clark, 1999). Patterns are similar across treatment groups, and words associated with the ecology were the largest category (averaging 35% of all words across all groups), followed by those related to destruction (around 17.5%) and negative affect (around 14%). Notably, Bats elicit more negative affect words associated with disgust, compared to Lions, who elicit more words associated with anger.

Appendix C

Data Appendix for Chapter 3

Table C.1: Description of variables

Variables	Description
Donations	Charitable donation decision from £0 to £25
Willingness to pay fee	WTP fee, 0-100 pence
Willingness to donate time	WTD time, 0-7 hours
Donor	Previously made donations to charity (No (0), Yes (1))
Pro-environmental behaviour (PEB)	Average PEB score (Minimum (0) to Maximum (4))
Age	Continuous, in years
Gender	Categorical, Male (0), Female (1)
Student	Categorical, Yes (1), No (0)
Subjects/session	Number of subjects per session (Maximum of 20)

Notes: Values in table Mean with standard deviation in brackets. P-values for Gender (% females), student status (% Full-time students), LSE, and Past donors are from the Pearson's chi-squared test. P-values for Age is from one-way Anova, and from PEB score, Hot beverages and Re-useable cps form Kruskal-Wallis equality-of-populations rank test. The null hypothesis in all tests, is that there is no difference across groups. As subjects were randomly assigned to different treatment groups in the lab, there imbalance on age and ht beverages is due to chance.

Table C.2: Summary statistics by treatment groups

Variables	All	No Video	Bats- Control Video	Bats- Cause Video	Lions- Control Video	Lions- Cause Video	Savanna- Control Video	Savanna- Cause Video	p-value
Panel A: Individual attributes									
% Female	63.707	61.111	62.857	65.714	68.421	55	68.421	64.865	0.896
Age (years)	24.405	24.472	27.429	22.514	24.316	24.3	23.842	24.054	0.016
	(7.73)	(8.28)	(8.72)	(5.09)	(7.78)	(8.18)	(6.14)	(8.88)	
% Full time students	80.309	77.778	71.429	91.429	68.421	87.5	78.947	86.486	0.114
% LSE	72.973	75	68.571	74.286	63.158	85	73.684	70.27	0.495
% Past donors	74.517	69.444	91.429	74.286	65.789	67.5	78.947	75.676	0.189
PEB score	1.775	1.917	1.848	1.714	1.728	1.667	1.877	1.685	0.496
	(0.74)	(0.81)	(0.62)	(0.76)	(0.77)	(0.78)	(0.73)	(0.72)	
Hot beverage drinkers	4.56	3.806	4.771	4.114	5.263	4.625	4.658	4.622	0.05
	(1.95)	(1.97)	(2.12)	(2.14)	(1.75)	(1.64)	(1.96)	(1.86)	
Re-useable cups	0.429	0.444	0.343	0.314	0.474	0.575	0.316	0.514	0.133
	(0.50)	(0.50)	(0.48)	(0.47)	(0.51)	(0.50)	(0.47)	(0.51)	
Sample size	259	36	35	35	38	40	38	37	
Panel B: Outcome variables									
Donations	8.722		6.771	9.057	10.079	9.875	6.395	10	
	(7.08)		(6.80)	(6.86)	(7.00)	(7.53)	(6.12)	(7.47)	
WTP	22.718	23	20.857	24.114	25.684	21.85	22.421	21.081	
	(21.47)	(21.10)	(20.52)	(18.23)	(24.08)	(20.70)	(22.67)	(23.48)	
WTD	2.34	2.306	2.229	2.143	2.368	2.75	2.316	2.216	
	(2.00)	(2.03)	(1.88)	(1.97)	(2.22)	(2.17)	(1.69)	(2.10)	

Notes: Values in table Mean with standard deviation in brackets. P-values for Gender (% females), student status (% Full-time students), LSE, and Past donors are from the Pearson's chi-squared test. P-values for Age is from one-way Anova, and from PEB score, Hot beverages and Re-useable cps form Kruskal-Wallis equality-of-populations rank test. The null hypothesis in all tests, is that there is no difference across groups. As subjects were randomly assigned to different treatment groups in the lab, there imbalance on age and ht beverages is due to chance.

Table C.3: Direct effect: Media content on donations (with individual controls)

	All		Sub-group analysis	
Hurdle type:	Probability	Amount	Probability	Amount
Hurdle models:	(1)	(2)	(3)	(4)
Cause = 1, Cause Video	0.249	2.282	0.19	-2.837
	(0.22)	(1.49)	(0.57)	(3.03)
Past Donor = 1, Yes			-0.407	-5.812**
			(0.41)	(2.56)
Cause Video X Past Donor			0.0725	6.991**
			(0.64)	(3.32)
Video = 1, Lions	0.516*	2.301	0.474*	1.541
	(0.27)	(1.77)	(0.27)	(1.77)
Video = 2, Savanna	0.0246	-0.63	0.00817	-0.737
	(0.25)	(1.72)	(0.25)	(1.62)
Age	-0.0169	-0.0082	-0.0169	0.017
	(0.02)	(0.12)	(0.02)	(0.11)
Gender = 1, Female	-0.0738	-1.119	-0.0775	-0.809
	(0.26)	(1.77)	(0.25)	(1.79)
Full-time student = 1, Yes	0.0127	5.538**	-0.00975	5.735**
	(0.34)	(2.45)	(0.34)	(2.42)
PEB	0.244	0.963	0.277	0.991
	(0.19)	(1.04)	(0.20)	(0.96)
Constant	7.259***	-0.712	8.595***	4.411
	(0.83)	(7.01)	(0.93)	(7.02)
Observations	223	223	223	223
Session controls	Yes	Yes	Yes	Yes
Video controls	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes

Notes: Robust standard errors clustered at subject-level in parentheses, *** p¡0.01, ** p¡0.05, * p¡0.1. Linear Cragg-hurdle model with donations is truncated at 0: the hurdle is modelled as a probit regression model, and the amount donated as a truncated linear regression. Session controls include subjects per session and session dummies. Video controls includes dummies for video type (i.e., bats, lions and savanna videos). Individual controls include age, dummies for gender and full-time student status, and PEB score.

Table C.4: Indirect effect: Media content on WTP green fee and WTD time (with individual controls)

Treatment effect:	Media exposure				Media content on Cause			
Outcome variable:	WTP		WTD		WTP		WTD	
Hurdle type:	Probability	Amount	Probability	Amount	Probability	Amount	Probability	Amount
Hurdle model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Media = 1, Control Video	4.065***	93.62*	0.421	0.773				
	(0.67)	(49.94)	(0.71)	(0.85)				
Media= 2, Cause Video	4.344***	93.78*	0.246	1.403	0.29	-2.015	0.661**	-0.162
	(0.67)	(49.85)	(0.73)	(0.90)	(0.31)	(12.05)	(0.31)	(0.20)
Past donor = 1, Yes			0.001	-0.135			0.009	0.0155
			(0.23)	(0.34)			(0.39)	(0.25)
PEB	0.703***	3.804	0.280**	0.619***	0.577**	2.777	0.770***	0.398***
	(0.21)	(8.27)	(0.13)	(0.19)	(0.24)	(9.35)	(0.21)	(0.15)
Age	-0.00766	-1.707*	-0.02	-0.0323	-0.0258	-1.491	-0.0329	-0.0142
	(0.03)	(0.99)	(0.02)	(0.02)	(0.03)	(1.11)	(0.02)	(0.02)
Gender = 1, Female	0.148	3.637	0.384*	0.472	0.371	-0.403	0.256	0.314
	(0.28)	(12.06)	(0.20)	(0.35)	(0.30)	(13.19)	(0.40)	(0.23)
Full-time student = 1, Yes	0.106	-14.11	-0.277	-1.262***	-0.196	-2.878	-1.386**	-0.147
	(0.43)	(20.02)	(0.32)	(0.47)	(0.58)	(21.34)	(0.54)	(0.36)
LSE = 1, Yes	0.31	-15.61	0.307	-0.289	0.149	-22.18	-0.117	0.144
	(0.32)	(14.44)	(0.27)	(0.39)	(0.36)	(16.67)	(0.43)	(0.30)
Hot beverages	-0.0767	0.717			-0.11	0.464		
	(0.07)	(3.00)			(0.10)	(3.64)		
Reusable cups	-0.0068	5.109			-0.0301	17.85		
	(0.31)	(11.56)			(0.33)	(13.26)		
Video = 1, Bats	0.959**	-1.5	0.156	-0.319				
	(0.40)	(14.77)	(0.25)	(0.39)				
Video = 2, Lions	0.456	5.314	0.146	0.105	-0.5	5.943	0.405	0.0198
	(0.33)	(14.02)	(0.25)	(0.37)	(0.42)	(14.44)	(0.43)	(0.25)
Video = 3, Savanna					-1.012**	1.208	0.291	-0.132
					(0.41)	(15.53)	(0.39)	(0.25)
Constant	-2.134	-460.4	-0.0336	-8.04	6.997***	-19.56	1.885	0.128
	(5.66)	(295.60)	(4.05)	(5.33)	(1.65)	(89.54)	(1.62)	(1.35)
Observations	259	259	259	259	223	223	223	223
Session, Video & Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors clustered at subject-level in parentheses, *** p¡0.01, ** p¡0.05, * p¡0.1. Linear Cragg-hurdle model with donations is truncated at 0: the hurdle is modelled as a probit regression model, and the amount donated as a truncated linear regression. In Models (1)-(4), No Video and Savanna-Control Video are omitted categories, and in Models (5)-(8), Control Video and Bats-Control Videos are omitted categories.

Table C.5: Heterogeneous spillover effects: Pro-social subjects as past donors (with individual controls)

Treatment effect:	Media exposure				Media content on Cause			
Outcome variable:	WTP		WTD		WTP		WTD	
Hurdle type:	Probability	Amount	Probability	Amount	Probability	Amount	Probability	Amount
Hurdle model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Media = 1, Control Video	4.810***	98.37**	0.43	0.971				
	(0.95)	(49.88)	(0.82)	(0.93)				
Media = 2, Cause Video	4.421***	83.68*	0.0519	-0.138	-0.38	-17.64	-0.383	-1.165*
	(0.76)	(49.26)	(0.82)	(1.01)	(0.59)	(24.84)	(0.46)	(0.67)
Past donor = 1, Yes	0.371	25.49	-0.163	-0.858	-0.327	15.59	-0.159	-1.089**
	(0.66)	(24.49)	(0.50)	(0.77)	(0.59)	(19.81)	(0.37)	(0.48)
Control Video X Past Donor	-0.631	-11.75	0.0277	-0.183				
	(0.88)	(29.59)	(0.62)	(0.90)				
Cause video X Past Donor	0.486	6.618	0.308	2.090**	1.121	20.98	0.3	2.386***
	(0.79)	(30.72)	(0.61)	(0.95)	(0.71)	(30.12)	(0.52)	(0.80)
PEB	0.727***	4.104	0.270**	0.624***	0.634***	5.256	0.391**	0.774***
	(0.20)	(8.13)	(0.14)	(0.19)	(0.24)	(10.30)	(0.15)	(0.21)
Age	-0.0125	-1.462	-0.0218	-0.0226	-0.0253	-1.201	-0.0145	-0.0235
	(0.02)	(0.92)	(0.02)	(0.02)	(0.03)	(1.06)	(0.02)	(0.02)
Gender = 1, Female	0.131	1.016	0.396*	0.33	0.336	-5.428	0.323	0.131
	(0.29)	(11.83)	(0.20)	(0.35)	(0.32)	(13.90)	(0.22)	(0.40)
Full-time student = 1, Yes	0.221	-20.77	-0.155	-1.330***	-0.0168	-13.42	-0.1	-1.363***
	(0.46)	(18.03)	(0.30)	(0.42)	(0.54)	(21.35)	(0.34)	(0.49)
Video = 1, Bats	0.977**	-1.741	0.173	-0.24				
	(0.41)	(14.54)	(0.25)	(0.37)				
Video = 2, Lions	0.437	8.869	0.161	0.0958	-0.578	12.45	0.00907	0.304
	(0.33)	(13.69)	(0.25)	(0.35)	(0.42)	(15.22)	(0.25)	(0.40)
Video = 3, Savanna					-1.052**	2.327	-0.152	0.222
					(0.42)	(15.94)	(0.25)	(0.38)
Constant	-2.292	-460.7*	0.0711	-8.069	6.096***	-32.72	0.293	2.502*
	(5.58)	(271.90)	(4.06)	(5.18)	(1.49)	(82.58)	(1.36)	(1.38)
Observations	259	259	259	259	223	223	223	223
Session, Video and Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors clustered at subject-level in parentheses, *** p¡0.01, ** p¡0.05, * p¡0.1. Linear Cragg-hurdle model with donations is truncated at 0: the hurdle is modelled as a probit regression model, and the amount donated as a truncated linear regression. In Models (1)-(4), No Video is the omitted category, and in Models (5)-(8), Control Video is the omitted category. Session controls include subjects per session and session fixed effects. Video controls includes dummies for video type (i.e., bats, lions and savanna videos). In Models (1)-(4), No Video and Savanna-Control Video are omitted categories, and in Models (5)-(8), Control Video and Bats-Control Videos are omitted categories.

Appendix D

Data Appendix for Chapter 4

D.0.1 Distribution of responses across risk measures

Figure D.1: Histogram of responses Binswanger-Eckel-Grossman lottery task (BEG)

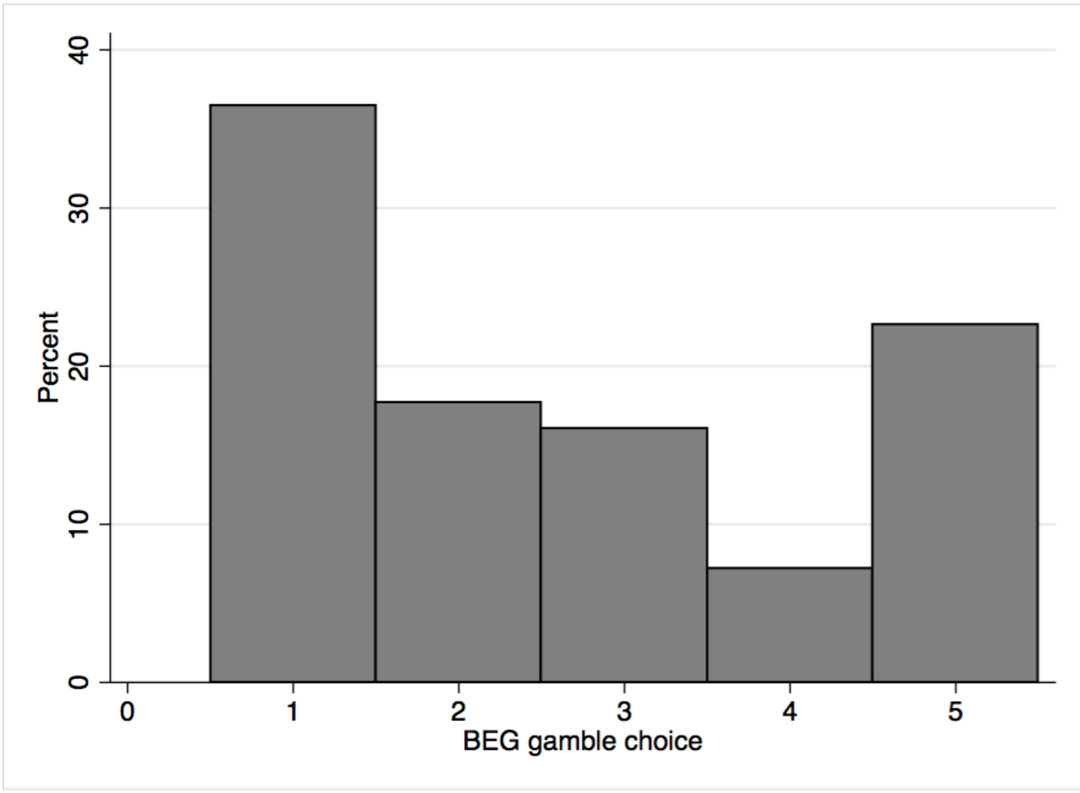
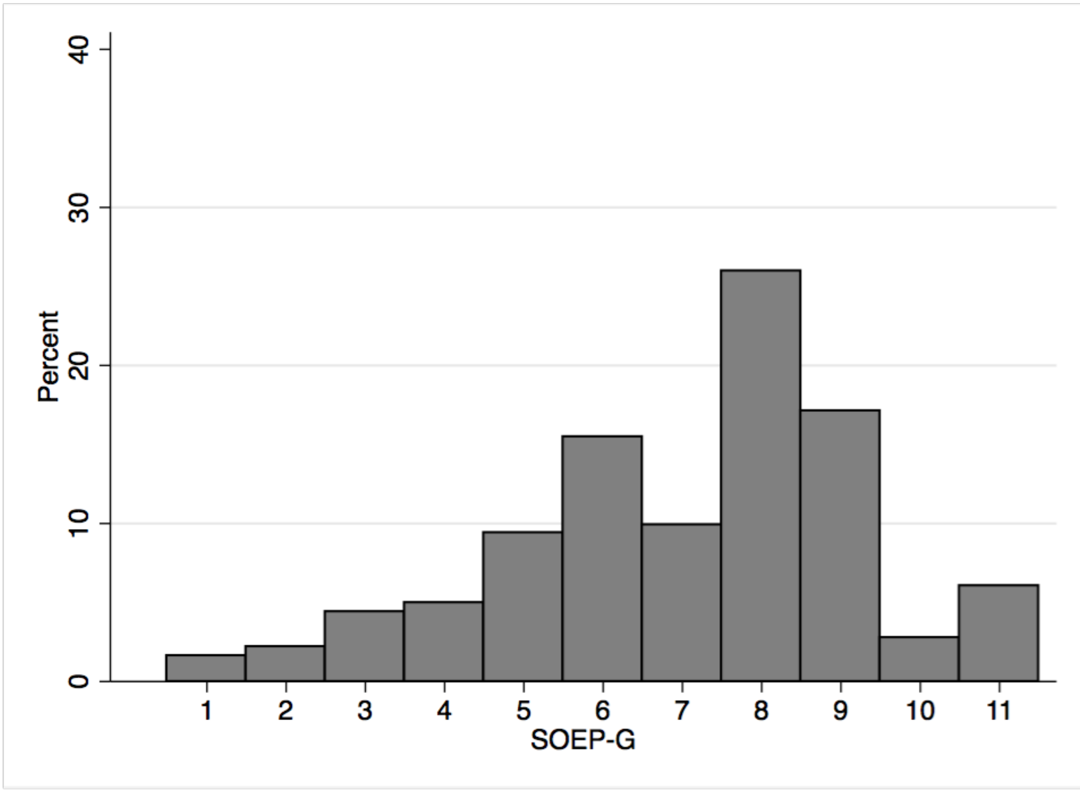
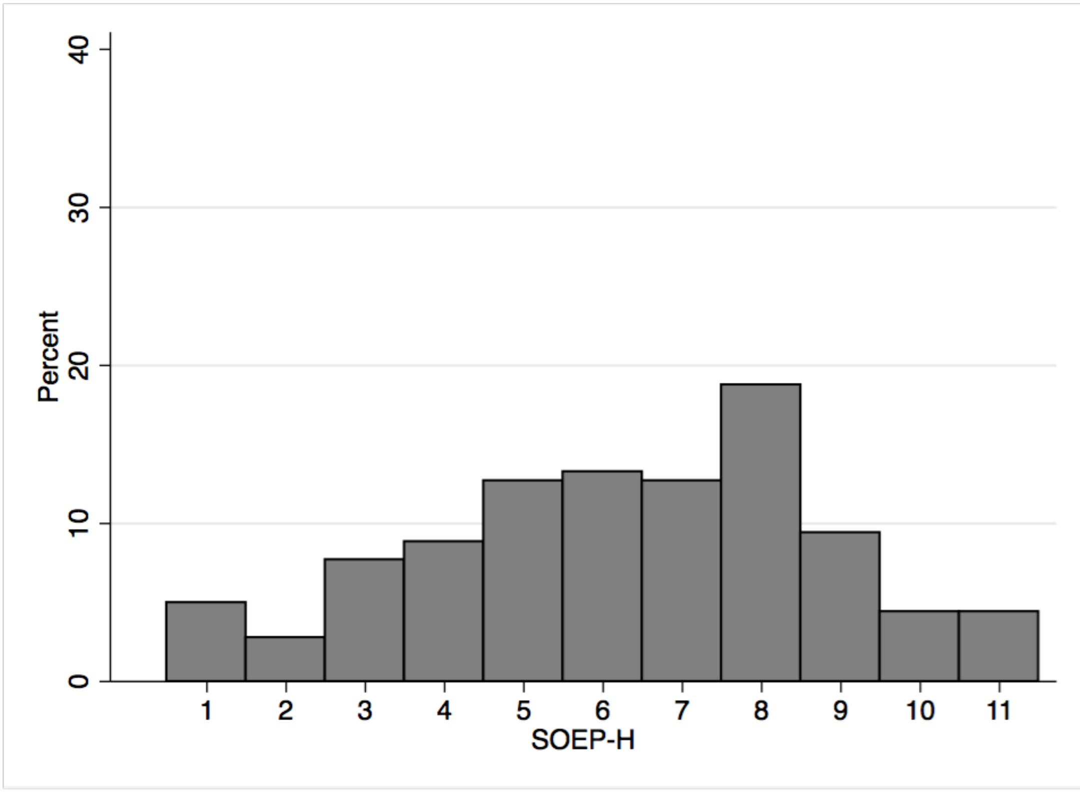


Figure D.2: Histogram of responses to General risk attitude measure (SOEP-G)



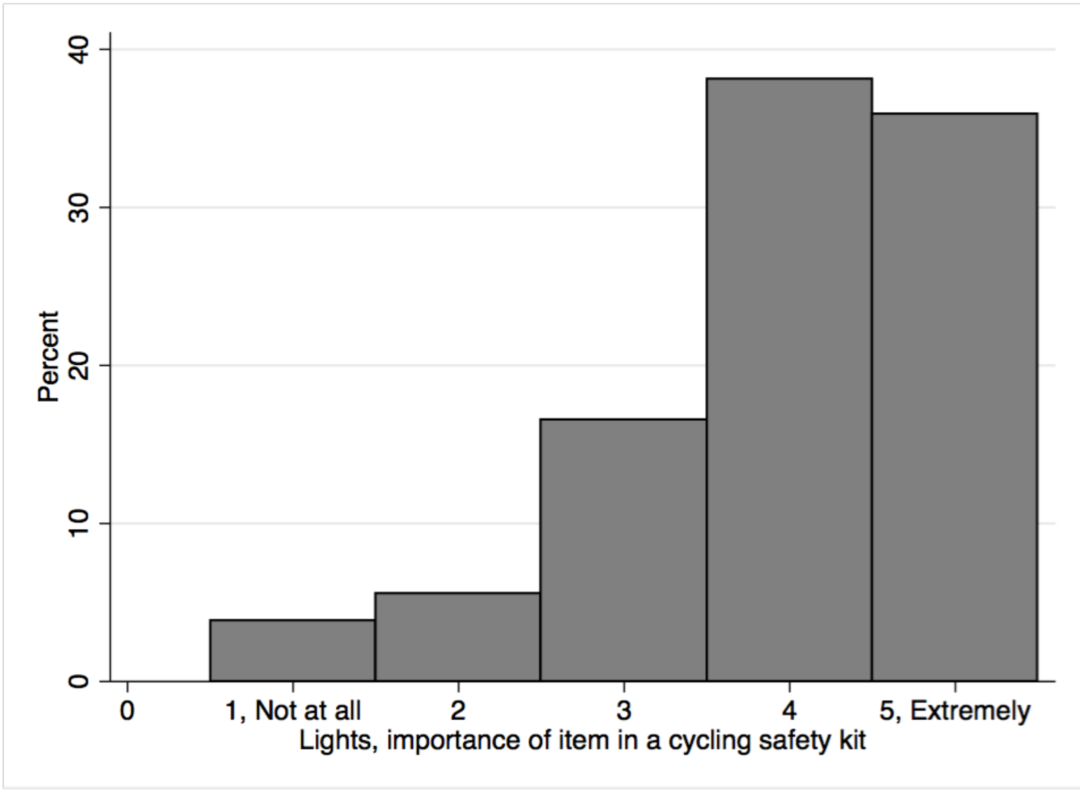
Notes: The SOEP-G question is recoded to take a minimum value of 1 and a maximum value of 11 from the original SOEP question.

Figure D.3: Histogram of responses to Health risk attitude measure (SOEP-H)



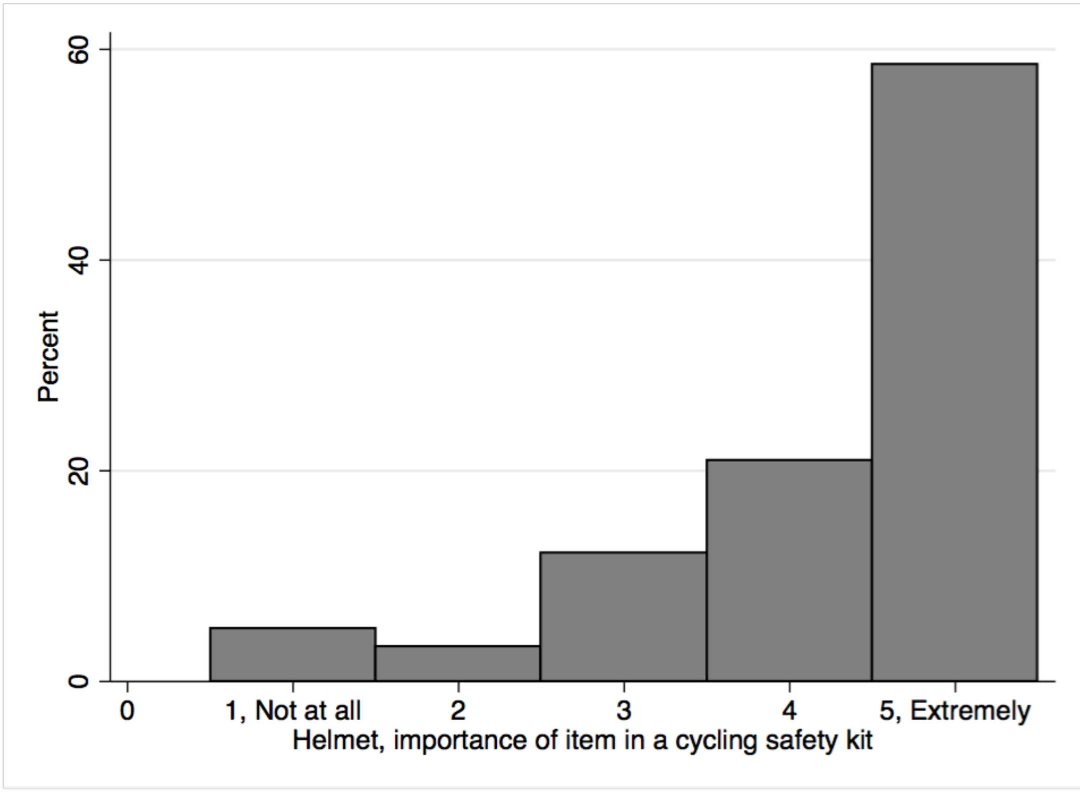
Notes: The SOEP-H question is recoded to take a minimum value of 1 and a maximum value of 11 from the original SOEP question.

Figure D.4: Histogram of responses to Lights (importance in cycling kit)



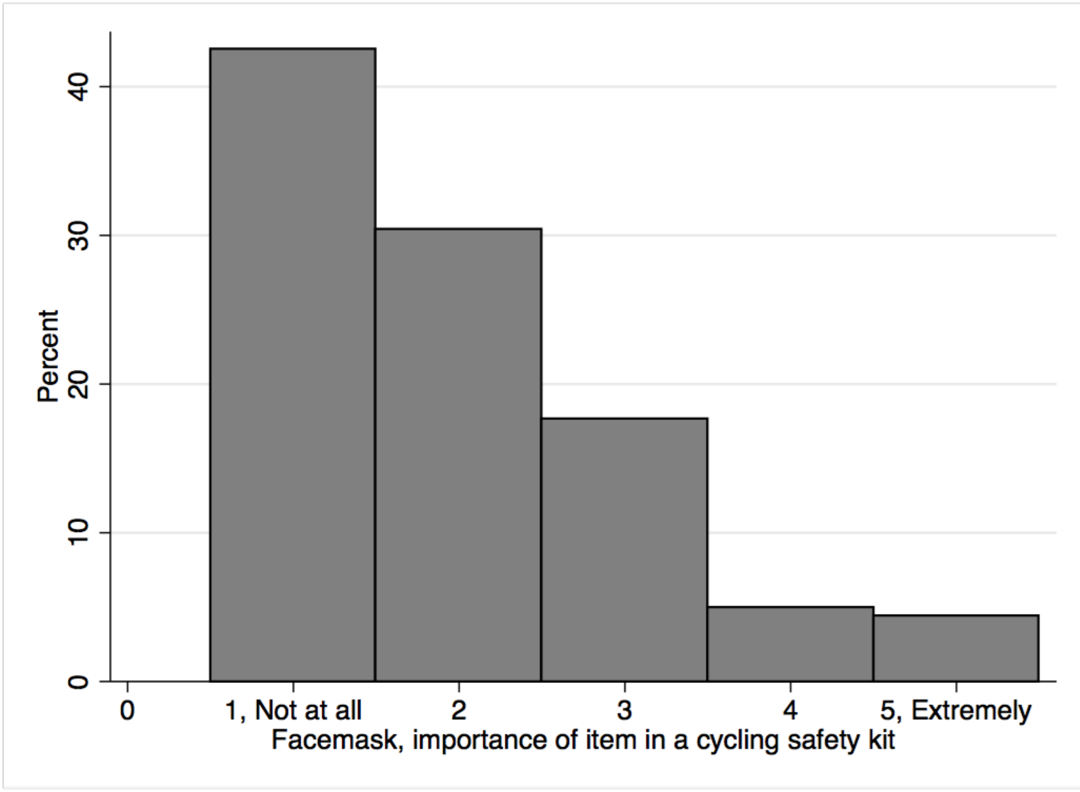
Notes: The question is reported in H.6 and the variable takes a minimum value of 1 and a maximum value of 5.

Figure D.5: Histogram of responses to Helmets (importance in cycling kit)



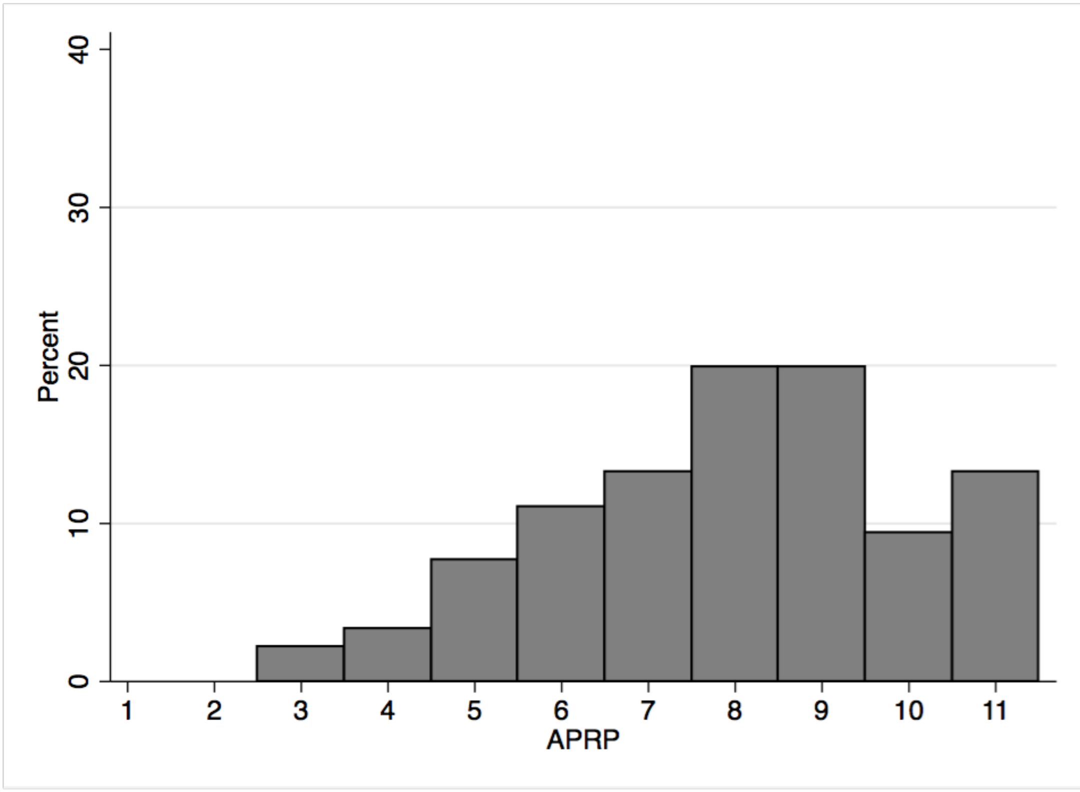
Notes: The question is reported in H.6 and the variable takes a minimum value of 1 and a maximum value of 5.

Figure D.6: Histogram of responses to Facemasks (importance in cycling kit)



Notes: The question is reported in H.6 and the variable takes a minimum value of 1 and a maximum value of 5.

Figure D.7: Histogram of responses to Air Pollution Risk Perception (APRP)



Notes: The question is reported in H.7 and the variable takes a minimum value of 1 and a maximum value of 11.

D.1 Behavioural validity I: Risk-taking

The results below provide the full specifications of the models in Chapter 4.

Table D.1: Risk measures and risk-taking while cycling: Full specifications

Dependent variable:	Risk-taking while cycling									
Ordered logistic models:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
BEG	0.104	0.147								
	(0.091)	(0.104)								
SOEP-G			0.125*	0.121*						
			(0.067)	(0.072)						
SOEP-H					0.197***	0.214***				
					(0.069)	(0.068)				
Lights							-0.492***	-0.485***		
							(0.127)	(0.147)		
Helmet									-0.625***	-0.791***
									(0.113)	(0.134)
Cyclist = 2, Com		-0.667		-0.756		-1.059		-0.850		-1.091*
		(0.700)		(0.649)		(0.678)		(0.655)		(0.636)
Cyclist = 3, Rec+Com		0.687		0.724		0.710		0.663		0.800*
		(0.457)		(0.449)		(0.467)		(0.448)		(0.419)
Cycle freq.		0.185		0.160		0.164		0.158		0.005
		(0.154)		(0.155)		(0.161)		(0.156)		(0.154)
Age = 2, 35-54		-0.774**		-0.750**		-0.767**		-0.647*		-0.908**
		(0.356)		(0.356)		(0.351)		(0.360)		(0.362)
Age = 3, >55		-0.932**		-0.844*		-0.823		-0.942**		-1.767***
		(0.457)		(0.490)		(0.515)		(0.477)		(0.484)
Gender = 2, Female		-0.576**		-0.532*		-0.489*		-0.328		-0.441
		(0.293)		(0.300)		(0.294)		(0.292)		(0.301)
Ethnicity = 2, BAMEO		0.524		0.460		0.494		0.543		0.680*
		(0.394)		(0.397)		(0.438)		(0.409)		(0.388)
Income = 2, £32k to ≤ £64k		-0.662		-0.587		-0.515		-0.622		-0.498
		(0.543)		(0.533)		(0.510)		(0.544)		(0.553)
Income = 3, >£64k		-1.234***		-1.125***		-1.116***		-1.067**		-0.972**
		(0.405)		(0.398)		(0.401)		(0.443)		(0.423)
Education = 2, UG		-0.136		-0.194		-0.281		-0.080		-0.008
		(0.442)		(0.437)		(0.453)		(0.470)		(0.471)
Education = 3, >UG		0.112		0.064		0.019		0.340		0.594
		(0.461)		(0.454)		(0.470)		(0.490)		(0.506)
Observations	181	181	181	181	181	181	181	181	181	181
Survey controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Dependent variable is the aggregate score of all risk-taking behaviours while cycling from 6 (‘Never’ for any behaviour) to 20 (‘Always’ for all behaviours). Independent variables include BEG: Binswanger-Eckel-Grossman risk measure; SOEP-G(H): German Socio-Economic Panel General (Health) risk attitude; Lights and Helmet: rating of importance of item in a cycling safety kit. The coefficients are the ordered log-odds (logit) regression coefficients, where the response variable level is expected to change by its respective regression coefficient in the ordered log-odds scale for a one unit increase in the predictor, while the other variables in the model are held constant. Individual controls include cyclist type, cycling frequency, air pollution knowledge, age, gender, ethnicity, income and education covariates. Omitted categories: Age: <35; Gender = Male; Ethnicity = White; Income: <£32k; Education: <UG. Abbreviations: BAMEO = Black Asian Minority Ethnic + Other, UG = Undergraduate degree. Survey controls include surveyor, location and time of day factor covariates. All models use robust standard errors. Significance levels reported at *** p<0.01, ** p<0.05, * p<0.1.

Table D.2: Risk measures and risk-taking behaviours I: Full specifications

Dependent variables:	Red lights					Music					No light				
Ordered logistic models:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
BEG	-0.011					0.114					-0.113				
	(0.110)					(0.116)					(0.122)				
SOEP-G		0.080					0.192*					0.145*			
		(0.092)					(0.107)					(0.088)			
SOEP-H			0.154*					0.201**					0.092		
			(0.079)					(0.083)					(0.081)		
Lights				-0.369**					-0.106					-0.504***	
				(0.174)					(0.172)					(0.192)	
Helmet					-0.387**					-0.076					-0.096
					(0.188)					(0.188)					(0.181)
Cyclist = 2, Com	0.771	0.831	0.702	0.755	0.729	-1.012	-0.959	-1.388	-1.037	-1.025	-0.682	-0.575	-0.719	-0.813	-0.696
	(0.679)	(0.674)	(0.680)	(0.646)	(0.650)	(0.843)	(0.965)	(1.024)	(0.866)	(0.865)	(0.833)	(0.840)	(0.885)	(0.917)	(0.881)
Cyclist = 3, Rec+Com	0.843*	0.866*	0.886*	0.846*	0.920**	0.037	0.240	0.163	0.091	0.102	0.785	0.815	0.780	0.745	0.767
	(0.460)	(0.467)	(0.479)	(0.447)	(0.453)	(0.501)	(0.521)	(0.512)	(0.499)	(0.502)	(0.537)	(0.547)	(0.558)	(0.546)	(0.533)
Cycle freq.	-0.141	-0.143	-0.158	-0.145	-0.215	0.655***	0.613***	0.651***	0.643***	0.627***	0.007	0.029	0.020	-0.008	0.000
	(0.169)	(0.169)	(0.174)	(0.168)	(0.173)	(0.241)	(0.233)	(0.251)	(0.241)	(0.238)	(0.209)	(0.211)	(0.212)	(0.222)	(0.213)
Age = 2, 35-54	0.017	0.047	0.045	0.096	-0.057	-0.914**	-0.840**	-0.900**	-0.919**	-0.937**	-0.586	-0.526	-0.563	-0.489	-0.602
	(0.345)	(0.355)	(0.350)	(0.346)	(0.341)	(0.404)	(0.404)	(0.404)	(0.400)	(0.394)	(0.404)	(0.406)	(0.410)	(0.413)	(0.399)
Age = 3, >55	-1.088**	-0.944	-0.896	-0.943*	-1.364**	-1.470*	-1.310	-1.431*	-1.551**	-1.621**	-1.783***	-1.525**	-1.631**	-1.579**	-1.746**
	(0.552)	(0.602)	(0.586)	(0.551)	(0.598)	(0.799)	(0.815)	(0.808)	(0.786)	(0.794)	(0.690)	(0.713)	(0.738)	(0.743)	(0.704)
Gender = 2, Female	-0.418	-0.368	-0.309	-0.202	-0.278	-0.484	-0.479	-0.349	-0.458	-0.488	-0.441	-0.362	-0.360	-0.087	-0.382
	(0.361)	(0.372)	(0.376)	(0.380)	(0.388)	(0.418)	(0.433)	(0.446)	(0.431)	(0.430)	(0.408)	(0.428)	(0.426)	(0.427)	(0.424)
Ethnicity = 2, BAMEO	-0.521	-0.541	-0.566	-0.504	-0.428	1.470***	1.330**	1.402**	1.449***	1.471***	0.015	-0.020	0.000	0.025	0.041
	(0.457)	(0.458)	(0.468)	(0.474)	(0.465)	(0.546)	(0.584)	(0.596)	(0.543)	(0.546)	(0.527)	(0.541)	(0.573)	(0.543)	(0.534)
Income = 2, £32k to $\leq$ £64k	-0.403	-0.422	-0.382	-0.431	-0.316	0.614	0.712	0.770	0.714	0.714	-0.254	-0.352	-0.294	-0.339	-0.314
	(0.592)	(0.594)	(0.621)	(0.600)	(0.640)	(0.689)	(0.691)	(0.685)	(0.705)	(0.713)	(0.749)	(0.816)	(0.781)	(0.808)	(0.765)
Income = 3, >£64k	-0.730	-0.726	-0.772	-0.623	-0.533	-0.331	-0.303	-0.356	-0.181	-0.199	-0.836	-0.940*	-0.936*	-0.753	-0.884*
	(0.463)	(0.464)	(0.486)	(0.462)	(0.520)	(0.636)	(0.616)	(0.646)	(0.643)	(0.652)	(0.522)	(0.512)	(0.531)	(0.537)	(0.521)
Education = 2, UG	0.601	0.585	0.567	0.686	0.661	-0.370	-0.592	-0.569	-0.354	-0.339	-1.151**	-1.231**	-1.215**	-1.110*	-1.125**
	(0.531)	(0.533)	(0.551)	(0.543)	(0.530)	(0.555)	(0.542)	(0.514)	(0.543)	(0.542)	(0.569)	(0.571)	(0.580)	(0.591)	(0.559)
Education = 3, >UG	0.662	0.610	0.602	0.865	0.825	0.139	-0.029	-0.053	0.217	0.217	-0.697	-0.821	-0.798	-0.463	-0.661
	(0.515)	(0.519)	(0.548)	(0.532)	(0.528)	(0.673)	(0.668)	(0.673)	(0.667)	(0.660)	(0.597)	(0.595)	(0.611)	(0.627)	(0.595)
Observations	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181
Survey controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable is the score of each risk-taking behaviour from 1 ('Never') to 5 ('Always'). Independent variables include BEG: Binswanger-Eckel-Grossman risk measure; SOEP-G(H): German Socio-Economic Panel General (Health) risk attitude; Lights and Helmet: rating of importance of item in a cycling safety kit. The coefficients are the ordered log-odds (logit) regression coefficients, where the response variable level is expected to change by its respective regression coefficient in the ordered log-odds scale for a one unit increase in the predictor, while the other variables in the model are held constant. Individual controls include cyclist type, cycling frequency, air pollution knowledge, age, gender, ethnicity, income and education covariates. Omitted categories: Age: <35; Gender = Male; Ethnicity = White; Income: $<$£32k; Education: $<$UG. Abbreviations: BAMEO = Black Asian Minority Ethnic + Other, UG = Undergraduate degree. Survey controls include surveyor, location and time of day factor covariates. All models use robust standard errors. Significance levels reported at *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table D.3: Risk measures and risk-taking behaviours II: Full specifications

Dependent variables:	(D) Mobile					(E) No helmet					(F) Alcohol				
Ordered logistic models:	(D1)	(D2)	(D3)	(D4)	(D5)	(E1)	(E2)	(E3)	(E4)	(E5)	(F1)	(F2)	(F3)	(F4)	(F5)
BEG	0.264**					0.012					0.167				
	(0.126)					(0.117)					(0.108)				
SOEP-G		0.172					-0.045					0.082			
		(0.123)					(0.078)					(0.074)			
SOEP-H			0.237***					0.124*					0.107		
			(0.086)					(0.074)					(0.073)		
Lights				-0.229					-0.355*					-0.240	
				(0.194)					(0.186)					(0.172)	
Helmet					-0.433**					-1.250***					-0.362**
					(0.219)					(0.238)					(0.172)
Cyclist = 2, Com	-1.845	-1.743	-2.274*	-1.865	-1.869	-0.489	-0.538	-0.602	-0.559	-0.987	-1.273	-1.261	-1.375*	-1.355	-1.415*
	(1.511)	(1.242)	(1.316)	(1.407)	(1.358)	(0.656)	(0.676)	(0.664)	(0.650)	(0.636)	(0.822)	(0.822)	(0.799)	(0.833)	(0.771)
Cyclist = 3, Rec+Com	-0.003	0.154	0.092	0.073	0.093	0.469	0.466	0.459	0.467	0.549	0.363	0.422	0.405	0.401	0.441
	(0.569)	(0.604)	(0.604)	(0.594)	(0.603)	(0.523)	(0.521)	(0.513)	(0.525)	(0.481)	(0.437)	(0.451)	(0.459)	(0.437)	(0.455)
Cycle freq.	0.322	0.271	0.245	0.284	0.180	0.045	0.037	0.047	0.044	-0.255	0.140	0.126	0.118	0.138	0.068
	(0.257)	(0.259)	(0.259)	(0.254)	(0.262)	(0.204)	(0.199)	(0.203)	(0.214)	(0.193)	(0.186)	(0.189)	(0.192)	(0.187)	(0.201)
Age = 2, 35-54	-1.163***	-1.117**	-1.175***	-1.141***	-1.343***	-0.479	-0.491	-0.486	-0.435	-0.727**	0.279	0.285	0.276	0.318	0.208
	(0.444)	(0.454)	(0.456)	(0.438)	(0.496)	(0.347)	(0.342)	(0.341)	(0.353)	(0.366)	(0.346)	(0.348)	(0.357)	(0.350)	(0.344)
Age = 3, >55	-2.306**	-2.242**	-2.510**	-2.401***	-2.724***	0.911	0.832	1.007	1.072*	0.467	-0.555	-0.545	-0.582	-0.602	-0.913
	(0.984)	(0.979)	(1.093)	(0.921)	(0.972)	(0.617)	(0.577)	(0.612)	(0.579)	(0.628)	(0.616)	(0.611)	(0.613)	(0.617)	(0.647)
Gender = 2, Female	-2.007***	-1.985***	-1.910***	-1.877***	-1.843***	-0.043	-0.072	0.028	0.189	0.432	-0.152	-0.135	-0.092	-0.070	-0.073
	(0.523)	(0.524)	(0.509)	(0.516)	(0.506)	(0.315)	(0.319)	(0.309)	(0.363)	(0.332)	(0.419)	(0.422)	(0.432)	(0.418)	(0.426)
Ethnicity = 2, BAMEO	-0.522	-0.727	-0.757	-0.576	-0.445	0.724*	0.731*	0.697*	0.716	1.110***	-0.669	-0.712	-0.741	-0.677	-0.628
	(0.733)	(0.721)	(0.744)	(0.677)	(0.674)	(0.411)	(0.409)	(0.419)	(0.436)	(0.402)	(0.535)	(0.553)	(0.560)	(0.543)	(0.550)
Income = 2, £32k to ≤ £64k	0.573	0.623	0.702	0.765	0.833	-1.523**	-1.510**	-1.518**	-1.590**	-1.923***	-0.099	-0.013	0.032	-0.007	0.048
	(0.856)	(0.895)	(0.864)	(0.916)	(0.865)	(0.627)	(0.626)	(0.614)	(0.636)	(0.670)	(0.622)	(0.626)	(0.632)	(0.639)	(0.661)
Income = 3, >£64k	-0.119	0.067	-0.004	0.215	0.398	-1.438***	-1.449***	-1.485***	-1.317**	-1.336**	-0.342	-0.212	-0.221	-0.161	-0.054
	(0.629)	(0.624)	(0.631)	(0.660)	(0.671)	(0.548)	(0.547)	(0.562)	(0.604)	(0.521)	(0.590)	(0.582)	(0.598)	(0.584)	(0.619)
Education = 2, UG	0.011	-0.029	-0.152	0.038	0.088	0.262	0.295	0.177	0.310	0.753	0.570	0.507	0.500	0.531	0.604
	(0.596)	(0.639)	(0.607)	(0.679)	(0.610)	(0.463)	(0.480)	(0.469)	(0.488)	(0.563)	(0.502)	(0.510)	(0.518)	(0.522)	(0.532)
Education = 3, >UG	-0.128	-0.212	-0.395	0.067	0.124	-0.088	-0.043	-0.179	0.062	0.885	0.747	0.675	0.678	0.822	0.906*
	(0.739)	(0.763)	(0.790)	(0.794)	(0.727)	(0.529)	(0.545)	(0.535)	(0.546)	(0.650)	(0.512)	(0.530)	(0.539)	(0.536)	(0.550)
Observations	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181
Survey controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable is the score of each risk-taking behaviour from 1 ('Never') to 5 ('Always'). Independent variables include BEG: Binswanger-Eckel-Grossman risk measure; SOEP-G(H): German Socio-Economic Panel General (Health) risk attitude; Lights and Helmet: rating of importance of item in a cycling safety kit. The coefficients are the ordered log-odds (logit) regression coefficients, where the response variable level is expected to change by its respective regression coefficient in the ordered log-odds scale for a one unit increase in the predictor, while the other variables in the model are held constant. Individual controls include cyclist type, cycling frequency, air pollution knowledge, age, gender, ethnicity, income and education covariates. Omitted categories: Age: <35; Gender = Male; Ethnicity = White; Income: <£32k; Education: <UG. Abbreviations: BAMEO = Black Asian Minority Ethnic + Other, UG = Undergraduate degree. Survey controls include surveyor, location and time of day factor covariates. All models use robust standard errors. Significance levels reported at *** p<0.01, ** p<0.05, * p<0.1.

D.2 Behavioural validity II: Avoidance

This section presents the full specifications of the regression models on risk measures and avoidance presented in the Chapter 4. Due to limited space, some notes about the regression models are presented here. First, the variables of risk measures include BEG: Binswanger-Eckel-Grossman risk measure; SOEP-G(H): German Socio-Economic Panel General (Health) risk attitude; Lights and Helmet: rating of importance of item in a cycling safety kit. Second, the coefficients are the ordered log-odds (logit) regression coefficients, where the response variable level is expected to change by its respective regression coefficient in the ordered log-odds scale for a one unit increase in the predictor, while the other variables in the model are held constant. Third, individual controls include cyclist type, cycling frequency, air pollution knowledge, age, gender, ethnicity, income and education covariates. Omitted categories: Age: <35; Gender = Male; Ethnicity = White; Income: <£32k; Education: <UG. Note the abbreviations: BAMEO = Black Asian Minority Ethnic + Other, UG = Undergraduate degree. Survey controls include surveyor, location and time of day factor covariates.

Table D.4: Risk measures and avoidance (aggregate): Full specifications

Dependent variable:	# Air pollution avoidance													
Poisson regression models	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
BEG	-0.005	-0.000												
	(0.036)	(0.036)												
SOEP-G			-0.011	-0.020										
			(0.027)	(0.027)										
SOEP-H					0.006	0.008								
					(0.024)	(0.021)								
Lights							0.068	0.091*						
							(0.051)	(0.055)						
Helmet									-0.012	0.020				
									(0.048)	(0.050)				
Facemask											0.188***	0.191***		
											(0.051)	(0.054)		
APRP													0.086***	0.088***
													(0.030)	(0.030)
Cyclist = 2, Com		-0.015		-0.040		-0.019		-0.012		-0.011		0.095		0.041
		(0.217)		(0.233)		(0.214)		(0.216)		(0.216)		(0.201)		(0.217)
Cyclist = 3, Rec+Com		-0.043		-0.051		-0.040		-0.038		-0.043		0.024		-0.050
		(0.142)		(0.142)		(0.143)		(0.142)		(0.143)		(0.151)		(0.149)
Cycle freq.		-0.034		-0.036		-0.035		-0.038		-0.031		-0.074		-0.050
		(0.064)		(0.064)		(0.064)		(0.062)		(0.065)		(0.064)		(0.063)
AP knowledge		0.139***		0.143***		0.139***		0.150***		0.141***		0.127***		0.137***
		(0.043)		(0.044)		(0.043)		(0.043)		(0.043)		(0.040)		(0.042)
Age = 2, 35-54		-0.119		-0.123		-0.119		-0.141		-0.116		-0.092		-0.089
		(0.130)		(0.130)		(0.130)		(0.131)		(0.130)		(0.119)		(0.124)
Age = 3, >55		0.152		0.125		0.157		0.105		0.162		0.272		0.196
		(0.191)		(0.187)		(0.186)		(0.188)		(0.184)		(0.181)		(0.192)
Gender = 2, Female		0.020		0.005		0.027		-0.026		0.014		-0.068		-0.033
		(0.142)		(0.145)		(0.143)		(0.144)		(0.142)		(0.138)		(0.141)
Ethnicity = 2, BAMEO		-0.163		-0.165		-0.164		-0.162		-0.166		-0.248		-0.216
		(0.160)		(0.161)		(0.161)		(0.162)		(0.161)		(0.159)		(0.164)
Income = 2, £32k to ≤ £64k		-0.090		-0.093		-0.087		-0.096		-0.094		-0.126		-0.145
		(0.186)		(0.184)		(0.185)		(0.180)		(0.186)		(0.172)		(0.184)
Income = 3, >£64k		-0.270		-0.278*		-0.270		-0.302*		-0.279*		-0.236		-0.228
		(0.170)		(0.168)		(0.169)		(0.164)		(0.167)		(0.157)		(0.169)
Education = 2, UG		-0.072		-0.066		-0.077		-0.096		-0.077		0.033		-0.040
		(0.162)		(0.159)		(0.161)		(0.158)		(0.164)		(0.155)		(0.160)
Education = 3, >UG		0.173		0.187		0.167		0.123		0.163		0.281		0.187
		(0.176)		(0.173)		(0.177)		(0.180)		(0.179)		(0.172)		(0.173)
Constant	0.288	0.342	0.341	0.479	0.243	0.303	-0.009	0.017	0.324	0.243	-0.120	0.005	-0.447	-0.310
	(0.294)	(0.400)	(0.319)	(0.426)	(0.298)	(0.392)	(0.358)	(0.442)	(0.358)	(0.468)	(0.304)	(0.394)	(0.370)	(0.450)
Observations	181	181	181	181	181	181	181	181	181	181	181	181	181	181
Survey controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Dependent variable is an event count from 0 (no avoidance) to 6 (6 types of avoidance behaviours). All models use robust standard errors. Significance levels reported at *** p<0.01, ** p<0.05, * p<0.1.

Table D.5: Risk measures and avoidance behaviours I: Full specifications

Dependent variables:	(A) Avoiding main roads							(B) Avoiding peak travel						
Logistic models:	(A1)	(A2)	(A3)	(A4)	(A5)	(A6)	(A7)	(B1)	(B2)	(B3)	(B4)	(B5)	(B6)	(B7)
BEG	-0.157							-0.215						
	(0.104)							(0.133)						
SOEP-G		-0.141*							-0.017					
		(0.077)							(0.093)					
SOEP-H			-0.065							0.125				
			(0.069)							(0.082)				
Lights				0.357**							-0.060			
				(0.175)							(0.207)			
Helmet					0.251							0.017		
					(0.166)							(0.183)		
Facemask						0.393**							0.738***	
						(0.175)							(0.241)	
APRP							0.093							0.138
							(0.083)							(0.107)
AP knowledge	0.135	0.147	0.121	0.172	0.157	0.095	0.117	0.449**	0.413**	0.419***	0.405**	0.411**	0.383**	0.417**
	(0.137)	(0.138)	(0.136)	(0.137)	(0.136)	(0.137)	(0.135)	(0.179)	(0.173)	(0.159)	(0.170)	(0.170)	(0.157)	(0.166)
Cyclist = 2, Com	0.313	0.230	0.381	0.429	0.420	0.534	0.397	0.159	0.209	0.134	0.222	0.221	0.531	0.302
	(0.779)	(0.800)	(0.783)	(0.803)	(0.763)	(0.829)	(0.794)	(0.949)	(0.885)	(0.849)	(0.864)	(0.880)	(0.822)	(0.884)
Cyclist = 3, Rec+Com	-0.358	-0.461	-0.414	-0.395	-0.408	-0.281	-0.398	-0.168	-0.251	-0.252	-0.247	-0.250	-0.017	-0.255
	(0.458)	(0.459)	(0.455)	(0.457)	(0.458)	(0.470)	(0.463)	(0.529)	(0.518)	(0.517)	(0.517)	(0.516)	(0.572)	(0.530)
Cycle freq.	0.141	0.162	0.175	0.157	0.212	0.099	0.155	-0.458*	-0.405*	-0.408*	-0.403*	-0.399*	-0.583**	-0.433*
	(0.190)	(0.189)	(0.191)	(0.187)	(0.194)	(0.198)	(0.192)	(0.258)	(0.240)	(0.234)	(0.238)	(0.237)	(0.238)	(0.244)
Age = 2, 35-54	0.171	0.134	0.171	0.113	0.219	0.263	0.215	-0.591	-0.592	-0.586	-0.573	-0.584	-0.506	-0.527
	(0.356)	(0.360)	(0.357)	(0.357)	(0.352)	(0.353)	(0.351)	(0.464)	(0.469)	(0.476)	(0.473)	(0.469)	(0.485)	(0.470)
Age = 3, >55	-0.252	-0.315	-0.153	-0.295	-0.010	0.147	-0.045	0.096	0.242	0.392	0.301	0.277	0.861	0.352
	(0.591)	(0.579)	(0.579)	(0.589)	(0.614)	(0.621)	(0.598)	(0.703)	(0.730)	(0.740)	(0.722)	(0.740)	(0.742)	(0.721)
Gender = 2, Female	0.296	0.252	0.294	0.145	0.270	0.189	0.269	-0.247	-0.198	-0.075	-0.147	-0.189	-0.570	-0.263
	(0.365)	(0.370)	(0.363)	(0.396)	(0.364)	(0.375)	(0.367)	(0.493)	(0.507)	(0.514)	(0.507)	(0.492)	(0.541)	(0.508)
Ethnicity = 2, BAMEO	-0.336	-0.299	-0.285	-0.322	-0.366	-0.475	-0.349	-0.229	-0.150	-0.137	-0.149	-0.148	-0.546	-0.197
	(0.452)	(0.466)	(0.453)	(0.464)	(0.463)	(0.466)	(0.456)	(0.482)	(0.496)	(0.512)	(0.490)	(0.492)	(0.539)	(0.503)
Income = 2, £32k to $\leq$ £64k	-1.024	-1.104*	-1.113*	-1.146*	-1.156*	-1.193*	-1.138*	-0.391	-0.441	-0.368	-0.435	-0.438	-0.542	-0.562
	(0.651)	(0.632)	(0.632)	(0.635)	(0.640)	(0.660)	(0.636)	(0.723)	(0.690)	(0.683)	(0.691)	(0.696)	(0.696)	(0.713)
Income = 3, >£64k	-0.671	-0.821	-0.761	-0.919*	-0.899*	-0.704	-0.729	-1.688***	-1.780***	-1.803***	-1.760***	-1.779***	-1.671***	-1.727***
	(0.526)	(0.518)	(0.510)	(0.513)	(0.506)	(0.511)	(0.521)	(0.628)	(0.636)	(0.642)	(0.633)	(0.626)	(0.636)	(0.657)
Education = 2, UG	-0.092	-0.001	-0.018	-0.111	-0.137	0.121	-0.017	0.275	0.346	0.265	0.373	0.333	0.780	0.387
	(0.473)	(0.464)	(0.467)	(0.463)	(0.493)	(0.482)	(0.469)	(0.670)	(0.657)	(0.659)	(0.695)	(0.665)	(0.717)	(0.653)
Education = 3, >UG	0.577	0.692	0.635	0.436	0.439	0.749	0.616	1.743**	1.768**	1.687**	1.807**	1.744**	2.276***	1.774**
	(0.527)	(0.516)	(0.517)	(0.522)	(0.535)	(0.521)	(0.519)	(0.728)	(0.718)	(0.715)	(0.784)	(0.737)	(0.742)	(0.716)
Constant	-1.256	-0.831	-1.429	-3.050**	-2.940**	-2.449**	-2.443*	-0.221	-0.735	-1.553	-0.654	-0.938	-2.231	-1.786
	(1.235)	(1.301)	(1.223)	(1.383)	(1.428)	(1.231)	(1.327)	(1.801)	(1.853)	(1.680)	(1.949)	(1.883)	(1.976)	(1.787)
Observations	181	181	181	181	181	181	181	181	181	181	181	181	181	181
Survey controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable is the score of each risk-taking behaviour from 1 ('Never') to 5 ('Always'). All models use robust standard errors. Significance levels reported at *** p<0.01, ** p<0.05, * p<0.1.

Table D.6: Risk measures and avoidance behaviours II: Full specifications

Dependent variables:	(C) Avoiding stopping behind vehicles							(B) Biking short distances						
Logistic models:	(C1)	(C2)	(C3)	(C4)	(C5)	(C6)	(C7)	(D1)	(D2)	(D3)	(D4)	(D5)	(D6)	(D7)
BEG	0.081							0.066						
	(0.109)							(0.113)						
SOEP-G		0.001							-0.024					
		(0.075)							(0.085)					
SOEP-H			-0.010							0.027				
			(0.065)							(0.074)				
Lights				0.019							0.201			
				(0.167)							(0.160)			
Helmet					0.099							-0.072		
					(0.161)							(0.167)		
Facemask						0.433**							-0.237	
						(0.189)							(0.188)	
APRP							0.171*							0.086
							(0.092)							(0.092)
AP knowledge	0.164	0.169	0.169	0.171	0.183	0.146	0.167	0.350**	0.358**	0.354**	0.378***	0.345**	0.376**	0.352**
	(0.138)	(0.137)	(0.137)	(0.138)	(0.139)	(0.140)	(0.141)	(0.139)	(0.142)	(0.140)	(0.143)	(0.141)	(0.146)	(0.140)
Cyclist = 2, Com	0.593	0.589	0.594	0.590	0.611	0.791	0.725	-0.823	-0.882	-0.870	-0.828	-0.875	-1.039	-0.797
	(0.760)	(0.742)	(0.744)	(0.741)	(0.747)	(0.773)	(0.743)	(0.779)	(0.802)	(0.765)	(0.779)	(0.782)	(0.843)	(0.782)
Cyclist = 3, Rec+Com	0.110	0.129	0.128	0.129	0.122	0.274	0.119	0.365	0.372	0.384	0.393	0.389	0.290	0.384
	(0.475)	(0.476)	(0.475)	(0.475)	(0.477)	(0.516)	(0.490)	(0.509)	(0.509)	(0.508)	(0.511)	(0.513)	(0.511)	(0.527)
Cycle freq.	-0.080	-0.090	-0.090	-0.091	-0.075	-0.172	-0.120	-0.110	-0.114	-0.118	-0.132	-0.127	-0.073	-0.134
	(0.193)	(0.192)	(0.192)	(0.192)	(0.196)	(0.201)	(0.193)	(0.213)	(0.210)	(0.213)	(0.210)	(0.214)	(0.214)	(0.216)
Age = 2, 35-54	-0.124	-0.127	-0.127	-0.131	-0.108	-0.077	-0.068	-0.204	-0.207	-0.208	-0.262	-0.218	-0.225	-0.181
	(0.341)	(0.341)	(0.340)	(0.343)	(0.341)	(0.346)	(0.337)	(0.362)	(0.362)	(0.362)	(0.365)	(0.363)	(0.365)	(0.361)
Age = 3, >55	1.514**	1.448*	1.440*	1.435*	1.501**	1.773**	1.545**	0.969	0.885	0.942	0.830	0.882	0.744	0.944
	(0.753)	(0.739)	(0.749)	(0.757)	(0.754)	(0.755)	(0.785)	(0.675)	(0.662)	(0.661)	(0.666)	(0.656)	(0.651)	(0.650)
Gender = 2, Female	0.175	0.156	0.148	0.146	0.123	0.007	0.035	-0.196	-0.236	-0.201	-0.321	-0.200	-0.140	-0.285
	(0.391)	(0.393)	(0.393)	(0.403)	(0.396)	(0.412)	(0.414)	(0.413)	(0.418)	(0.419)	(0.429)	(0.420)	(0.424)	(0.432)
Ethnicity = 2, BAMEO	-0.646	-0.664	-0.662	-0.666	-0.691	-0.870*	-0.786	0.151	0.142	0.135	0.125	0.158	0.226	0.108
	(0.472)	(0.472)	(0.472)	(0.471)	(0.474)	(0.507)	(0.502)	(0.432)	(0.434)	(0.432)	(0.431)	(0.443)	(0.446)	(0.443)
Income = 2, £32k to ≤ £64k	0.061	0.108	0.105	0.109	0.095	0.049	0.055	0.052	0.076	0.101	0.095	0.095	0.138	0.036
	(0.607)	(0.597)	(0.597)	(0.596)	(0.601)	(0.620)	(0.624)	(0.624)	(0.622)	(0.621)	(0.615)	(0.624)	(0.627)	(0.622)
Income = 3, >£64k	0.039	0.093	0.094	0.084	0.039	0.188	0.149	-0.219	-0.188	-0.171	-0.253	-0.138	-0.227	-0.152
	(0.516)	(0.506)	(0.507)	(0.513)	(0.511)	(0.520)	(0.514)	(0.555)	(0.550)	(0.552)	(0.546)	(0.573)	(0.569)	(0.546)
Education = 2, UG	-0.016	-0.022	-0.015	-0.023	-0.045	0.156	0.052	-0.471	-0.464	-0.499	-0.508	-0.468	-0.584	-0.444
	(0.463)	(0.466)	(0.468)	(0.463)	(0.466)	(0.498)	(0.484)	(0.470)	(0.474)	(0.475)	(0.467)	(0.473)	(0.481)	(0.475)
Education = 3, >UG	-0.279	-0.279	-0.270	-0.286	-0.330	-0.141	-0.233	0.088	0.111	0.070	-0.000	0.128	0.018	0.135
	(0.496)	(0.503)	(0.502)	(0.505)	(0.507)	(0.520)	(0.519)	(0.545)	(0.551)	(0.552)	(0.552)	(0.556)	(0.554)	(0.552)
Constant	0.103	0.314	0.368	0.254	-0.157	-0.443	-0.986	-1.526	-1.200	-1.475	-2.044	-0.999	-0.948	-1.979
	(1.124)	(1.185)	(1.126)	(1.208)	(1.345)	(1.157)	(1.290)	(1.191)	(1.228)	(1.185)	(1.264)	(1.361)	(1.190)	(1.368)
Observations	177	177	177	177	177	177	177	172	172	172	172	172	172	172
Survey controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable is the score of each risk-taking behaviour from 1 (Never) to 5 (Always). All models use robust standard errors. Significance levels reported at *** p<0.01, ** p<0.05, * p<0.1.

D.3 Cross-context validity

Table D.7: Cross-stability I: BEG, SOEP-G and SOEP-H

Dependent variables:	BEG	SOEP-G			SOEP-H		
Ordered probit regressions:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
BEG		0.107**	0.123**	0.122**	0.066	0.090*	0.075
		(0.049)	(0.050)	(0.055)	(0.048)	(0.049)	(0.053)
Age = 2, 35-54	-0.060			-0.171			-0.045
	(0.188)			(0.166)			(0.171)
Age = 3, >55	-0.630**			-0.547			-0.342
	(0.306)			(0.353)			(0.307)
Gender = 2, Female	-0.187			-0.267			-0.319*
	(0.196)			(0.180)			(0.175)
Ethnicity = 2, BAMEO	-0.101			0.176			0.108
	(0.209)			(0.258)			(0.235)
Income = 2, £32k to ≤ £64k	0.413			-0.053			-0.183
	(0.300)			(0.293)			(0.282)
Income = 3, >£64k	0.462*			-0.148			-0.053
	(0.238)			(0.229)			(0.222)
Education = 2, UG	-0.075			0.218			0.200
	(0.236)			(0.234)			(0.241)
Education = 3, >UG	-0.015			0.362			0.285
	(0.279)			(0.243)			(0.256)
Observations	181	181	181	181	181	181	181
Survey controls	Yes	No	Yes	Yes	No	Yes	Yes
Individual controls	Yes	No	No	Yes	No	No	Yes

Notes: Dependent variable is the score of each risk-taking behaviour from 1 (Never) to 5 (Always). All models use robust standard errors. Significance levels reported at *** p<0.01, ** p<0.05, * p<0.1.

Table D.8: Cross-context validity II: Lights, Helmet and Facemasks

Dependent variables:	(A) Lights			(B) Helmets			(C) Facemask			
Ordered probit models:	(A1)	(A2)	(A3)	(B1)	(B2)	(B3)	(C1)	(C2)	(C3)	(C4)
BEG	-0.031			-0.026			0.006			
	(0.056)			(0.060)			(0.054)			
SOEP-G		-0.002			-0.011			0.034		
		(0.042)			(0.048)			(0.045)		
SOEP-H			0.050			-0.062			0.037	
			(0.036)			(0.041)			(0.040)	
APRP										0.209***
										(0.060)
AP knowledge							0.077	0.073	0.081	0.066
							(0.074)	(0.075)	(0.074)	(0.074)
Cyclist = 2, Com	-0.249	-0.247	-0.274	-0.444	-0.452	-0.414	-0.546	-0.517	-0.569	-0.434
	(0.369)	(0.376)	(0.379)	(0.360)	(0.364)	(0.350)	(0.377)	(0.366)	(0.371)	(0.368)
Cyclist = 3, Rec+Com	-0.075	-0.084	-0.075	0.028	0.019	0.019	-0.452*	-0.437*	-0.446*	-0.489*
	(0.258)	(0.257)	(0.256)	(0.286)	(0.288)	(0.287)	(0.257)	(0.250)	(0.256)	(0.250)
Cycle freq.	0.054	0.058	0.054	-0.213**	-0.212**	-0.211**	0.209**	0.210**	0.207**	0.195**
	(0.101)	(0.101)	(0.101)	(0.107)	(0.105)	(0.106)	(0.104)	(0.101)	(0.102)	(0.096)
Age = 2, 35-54	0.250	0.252	0.261	-0.305	-0.302	-0.311	-0.157	-0.144	-0.152	-0.081
	(0.176)	(0.178)	(0.176)	(0.189)	(0.193)	(0.194)	(0.192)	(0.192)	(0.192)	(0.186)
Age = 3, >55	0.480	0.506	0.557	-0.665*	-0.656*	-0.696*	-0.750**	-0.723**	-0.744**	-0.689**
	(0.386)	(0.387)	(0.384)	(0.377)	(0.368)	(0.373)	(0.329)	(0.327)	(0.324)	(0.344)
Gender = 2, Female	0.714***	0.719***	0.764***	0.488**	0.486**	0.467**	0.460**	0.480**	0.491**	0.332*
	(0.216)	(0.217)	(0.219)	(0.204)	(0.205)	(0.201)	(0.205)	(0.212)	(0.215)	(0.201)
Ethnicity = 2, BAMEO	-0.013	-0.008	-0.013	0.228	0.233	0.226	0.516**	0.515**	0.509**	0.432*
	(0.207)	(0.206)	(0.199)	(0.267)	(0.266)	(0.279)	(0.230)	(0.229)	(0.229)	(0.232)
Income = 2, £32k to $\leq$ £64k	-0.029	-0.046	-0.031	0.078	0.067	0.041	0.078	0.072	0.087	0.023
	(0.340)	(0.342)	(0.348)	(0.325)	(0.326)	(0.320)	(0.333)	(0.330)	(0.330)	(0.324)
Income = 3, >£64k	0.433	0.409	0.410	0.540*	0.515*	0.529*	-0.275	-0.264	-0.273	-0.222
	(0.290)	(0.292)	(0.291)	(0.305)	(0.304)	(0.307)	(0.298)	(0.294)	(0.293)	(0.289)
Education = 2, UG	0.038	0.046	0.018	0.061	0.071	0.093	-0.529*	-0.549*	-0.556*	-0.472*
	(0.262)	(0.261)	(0.267)	(0.276)	(0.280)	(0.277)	(0.284)	(0.289)	(0.290)	(0.267)
Education = 3, >UG	0.386	0.392	0.358	0.387	0.399	0.434	-0.359	-0.389	-0.393	-0.306
	(0.272)	(0.273)	(0.276)	(0.294)	(0.301)	(0.298)	(0.286)	(0.285)	(0.287)	(0.269)
Observations	181	181	181	181	181	181	181	181	181	181
Survey controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable is self-assessment of importance of items in cycling kit (Lights/Helmets/Facemask) from 1 ('Not at all important') to 5 ('Extremely important'). All models use robust standard errors. Significance levels reported at *** p<0.01, ** p<0.05, * p<0.1.

Table D.9: Cross-context validity III: Air pollution risk perception and risk measures

Ordered probit models:	(1)	(2)	(3)	(4)	(5)	(6)
BEG	-0.019					
	(0.053)					
SOEP-G		0.087**				
		(0.040)				
SOEP-H			0.034			
			(0.035)			
Lights				0.086		
				(0.082)		
Helmet					0.099	
					(0.070)	
Facemask						0.436***
						(0.107)
AP knowledge	0.041	0.028	0.040	0.050	0.055	0.011
	(0.072)	(0.075)	(0.073)	(0.073)	(0.076)	(0.072)
Age = 2, 35-54	-0.205	-0.168	-0.199	-0.223	-0.181	-0.170
	(0.175)	(0.178)	(0.175)	(0.176)	(0.177)	(0.170)
Age = 3, >55	-0.475*	-0.337	-0.429	-0.502*	-0.412	-0.226
	(0.283)	(0.285)	(0.284)	(0.288)	(0.286)	(0.291)
Gender = 2, Female	0.393**	0.463**	0.425**	0.349*	0.368**	0.278
	(0.188)	(0.189)	(0.188)	(0.188)	(0.186)	(0.182)
Ethnicity = 2, BAMEO	0.281	0.286	0.280	0.278	0.260	0.144
	(0.232)	(0.229)	(0.233)	(0.235)	(0.235)	(0.233)
Income = 2, £32k to $\leq$ £64k	0.243	0.238	0.249	0.229	0.208	0.239
	(0.306)	(0.316)	(0.311)	(0.304)	(0.303)	(0.305)
Income = 3, >£64k	-0.223	-0.217	-0.232	-0.273	-0.298	-0.129
	(0.256)	(0.253)	(0.254)	(0.250)	(0.255)	(0.250)
Education = 2, UG	-0.185	-0.229	-0.200	-0.195	-0.203	-0.048
	(0.250)	(0.253)	(0.249)	(0.249)	(0.251)	(0.237)
Education = 3, >UG	-0.133	-0.201	-0.156	-0.169	-0.178	-0.021
	(0.281)	(0.283)	(0.280)	(0.281)	(0.285)	(0.270)
Observations	181	181	181	181	181	181
Survey controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable is Air pollution Risk Perception (APRP) from 1 (‘No risk at all’) to 11 (‘Extreme risk’). All models use robust standard errors. Significance levels reported at *** p<0.01, ** p<0.05, * p<0.1.

Appendix E

Data Appendix for Chapter 5

E.1 Sample characteristics and balance tests

Table E.1: Balance on covariates I (with sample characteristics)

Variables	Categories	All		Control group		Treatment group		Test of equality
		% Share (1)	Mean (s.d.) (2)	% Share (3)	Mean (s.d.) (4)	% Share (5)	Mean (s.d.) (6)	p-value (7)
Perceived Air Quality- London (PAQL)			1.337		1.177		1.494	[0.433]
			(1.309)		(0.110)		(0.159)	
Air pollution knowledge			2.938		2.923		2.933	[0.891]
			(1.243)		(1.267)		(1.225)	
Cyclist type	Recreational	24.860	1.75	25.560	1.758	24.180	1.744	[0.830]
	Rec./Commuter	75.140	(0.433)	74.440	(0.431)	75.820	(0.439)	
Cycle frequency	<1 pm	2.210	4.09	2.220	4.132	2.200	4.056	[0.480]
	1-2 pm	8.840	(1.037)	10.000	(1.046)	7.690	(1.032)	
	1 pw	9.390		6.670		12.090		
	2-4 pw	36.460		42.220		30.770		
	$\geq$ 5 pw	43.090		38.890		47.250		
Age	18 - 34 years	37.020	1.77	41.110	1.758	32.970	1.778	[0.608]
	35 - 54 years	50.830	(0.700)	42.220	(0.621)	59.340	(0.776)	
	$\geq$ 55	10.497		14.444		6.593		
	PNTS	1.657		2.222		1.099		
Gender	Male	66.300	1.36	65.560	1.330	67.030	1.389	[0.360]
	Female	32.600	(0.546)	32.220	(0.473)	32.970	(0.612)	
	PNTS	1.100		2.220		0.000		
Ethnicity	White	76.800	1.30	76.670	1.319	76.920	1.289	[0.605]
	BAME	16.020	(0.598)	17.780	(0.630)	14.290	(0.566)	
	PNTS	7.180		5.560		8.790		
Income	<£32k	22.380	2.66	24.660	2.692	20.000	2.633	[0.761]
	£32k to <£64k	16.780	(0.938)	10.960	(0.939)	22.860	(0.942)	
	$\geq$ £64k	41.960		49.320		34.290		
	DK/PNTS	18.880		15.070		22.860		
Education	<UG	20.99	2.14	20	2.099	21.98	2.178	[0.507]
	UG	48.07	(0.787)	46.67	(0.775)	49.45	(0.801)	
	>UG	27.07		28.89		25.27		
	PNTS	3.87		4.44		3.3		
Sample size		181		90		91		

Notes: The table presents the % share of the sample falling in each category of the covariate, with the means, and standard deviation in parentheses. The p-value (in square parentheses) test on the test of equality is based on the null hypothesis of no difference in the observed proportions for a variable between the control and treatment groups using a Pearson chi-squared test (Gender, Cyclist type, Ethnicity, categorical variables) or Wilcoxon-Mann-Whitney test (PAQL, Air pollution knowledge, Age, Eduction, Income, ordinal variables). PAQL: Perceived Air Quality in London, pm: per month, pw: per week, DK/PNTS: Don't know/Prefer not to say, BAMEO = Black Asian, minority ethnic + Other, UG = Undergraduate degree.

Table E.2: Balance on covariates I (other pre-treatment baseline variables)

Covariates	p-value
BEG risk preferences	0.199
SOEP-G, general willingness to take risk	0.529
SOEP-H, willingness to take health risks	0.675
Importance of lights in a cycling kit	0.809
Importance of helmets in a cycling kit	0.703
Importance of facemasks in a cycling kit	0.114
Air pollution risk perception	0.661
Surveyor	0.739
Location	0.366
Time of day	0.494

Notes: The p-value (in square parentheses) test on the test of equality is based on the null hypothesis of no difference in the observed proportions for a variable between the control and treatment groups using a Pearson chi-squared test (Surveyor, Location, Time of day, categorical variables), Wilcoxon-Mann-Whitney test (BEG risk, Lights, Helmets, Facemasks, 5-point scale, ordinal variables) or a t-test (SOEP-G, SOEP-H and Air pollution risk perception, 11-point scale ordinal variable).

E.2 Robustness checks

Table E.3: Heterogeneous treatment effects: Perceived Air Quality in London (PAQL), with individual controls

Treatment effect by sample: Logit model:	ATE (1)	ATT (2)
Treat = 1, Social norms	1.530**	1.586**
	(0.695)	(0.756)
High PAQL = 1, Optimistic about air quality = 1, 1-	0.628	0.596
	(0.611)	(0.641)
Treat (=1) x High PAQL (=1)	-1.542*	-1.436*
	(0.803)	(0.861)
AP knowledge	-0.097	-0.105
	(0.157)	(0.168)
Age = 2, 35-54	0.073	0.242
	(0.384)	(0.423)
Age = 3, >55	-0.761	-0.674
	(0.656)	(0.650)
Gender = 2, Female	0.541	0.630
	(0.425)	(0.443)
Ethnicity = 2, BAMEO	0.268	0.347
	(0.473)	(0.532)
Income = 2, £32k to < £64k	0.147	-0.274
	(0.599)	(0.635)
Income = 3, ≥ £64k	-0.721	-1.093**
	(0.530)	(0.549)
Income = 4, DK/PNTS	-1.174*	-1.631**
	(0.683)	(0.728)
Education = 2, UG	-1.052**	-1.247**
	(0.478)	(0.523)
Education = 3, >UG	0.022	-0.018
	(0.530)	(0.547)
Education = 4, PNTS	-0.454	-0.368
	(0.993)	(1.027)
Constant	-0.841	-0.225
	(0.991)	(1.109)
Observations	177	160
Survey dummies	Yes	Yes

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Binary outcome variable of choice of face-mask (or not). Independent variable: exposure to normative message. Moderator variable: Binary variable of Perceived air quality in London (High or Low PAQL). The logistic regression coefficients give the change in the log odds of the outcome for a one unit increase in the predictor variable. Surveyor dummies include surveyor and location dummies. ATE= Average treatment effect, ATT= Average treatment effect on treated. 4 observations dropped upon the addition of controls due to quasi-separation.

Table E.4: Heterogeneous treatment effects: Perceived Air Quality in London (PAQL), sub-group analysis

Treatment effect by sample:	ATE		ATT	
Logit models:	(1)	(2)	(3)	(4)
Treat = 1, Social norms	1.810**	1.826*	1.909**	6.532**
	(0.721)	(1.014)	(0.746)	(3.006)
AP knowledge		-0.581		0.500
		(0.457)		(0.803)
Age = 2, 35-54		-0.031		0.194
		(0.981)		(1.246)
Age = 3, >55		0.896		4.989**
		(1.978)		(2.499)
Gender = 2, Female		0.996		1.218
		(0.954)		(1.779)
Ethnicity = 2, BAMEO		0.287		6.560*
		(1.274)		(3.639)
Income = 2, £32k to < £64k		1.181		1.409
		(1.434)		(1.340)
Income = 3, $>\leq$ 64k		-0.887		-1.539
		(1.177)		(1.344)
Education = 2, UG		-1.614		-4.885**
		(1.117)		(2.196)
Education = 3, >UG		-0.351		-2.923
		(0.911)		(1.931)
Constant	-1.740	0.675	-0.955	-2.293
	(1.274)	(2.111)	(1.428)	(4.787)
Observations	50	46	45	41
Survey dummies	Yes	Yes	Yes	Yes
Individual controls	No	Yes	No	Yes

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Binary outcome variable of choice of face-mask (or not). Independent variable: exposure to normative message. Sample restricted to those optimistic about air quality, i.e., those who reported above median PAQL. The logistic regression coefficients give the change in the log odds of the outcome for a one unit increase in the predictor variable. Surveyor dummies include surveyor and location dummies. Four observations dropped due to quasi-separation.

Appendix F

Data Appendix for Chapter 6

Table F.1: Experimental parameters in relation to CPR literature

Features	OGW 1994	AMR 2006*	KL 2014*	CG 2015	Experiment
Endowment	25	100	50	12	25
a	23	6	6	18	25
b	0.25	0.0125	0.25	0.4	0.25
w	5	1	1	2	5
Group size (n)	8	4	4	4	4
Fee-to-Fine Ratio	0.25 to 0.50	-	-	0.33	0.33
-tokens	8	80	40	8	16
-payoff	70	180	112.5	37.6	189
-tokens	4.5	50	25	5	10
-payoff	83	225	90	52	225
Nash (N)/Pareto (P) tokens	1.8	1.6	1.6	1.6	1.6
N%P payoff	84	80	80	72	84

Notes: OGW 1994: Ostrom, Gardner, and Walker (1994); CG2015: Cason and Gangadharan (2015); AMR2006: Apesteguia and Maier-Rigaud (2006); KL 2014: Kingsley and Liu (2014); Experiment refers to our study. * No punishment.

References

Apesteguia, J., and Maier-Rigaud, F. P. (2006). The role of rivalry: public goods versus common-pool resources. Journal of Conflict Resolution, 50(5), 646-663.

Cason, T. N., and Gangadharan, L. (2015). Promoting cooperation in nonlinear social dilemmas through peer punishment. Experimental Economics, 18(1), 66-88.

Kingsley, D. C., and Liu, B. (2014). Cooperation across payoff equivalent public good and common pool resource experiments. Journal of Behavioral and Experimental Economics, 51, 79-84.

Ostrom, E., Gardner, R., and Walker, J. (1994). Rules, games, and common-pool resources. University of Michigan Press.

Table F.2: Individual attributes by treatment (%)

Individual control variables	Category	All	Complete	Undirected circle	Directed circle	Directed line	p-value
Sex = 2	Female	59.38	55	55.56	67.5	60.71	[0.608]
Economics = 1	Yes	16.15	15	16.67	17.5	16.07	[0.989]
Experience = 1	0	26.04	15	36.11	32.5	26.79	
Experience = 2	1 to 5	46.35	45	50	37.5	51.79	[0.170]
Experience = 3	6 to 10	17.19	25	8.33	20	12.5	
Experience = 4	Over 10	10.42	15	5.56	10	8.93	
Number of Sessions		10	3	2	2	3	
Number of Groups		720	225	135	150	210	
Number of Subjects		192	60	36	40	56	

Notes: The p-values give the significance level of the Pearson $\chi 2$ test for the independence.

Table F.3: Effect of beliefs on appropriation by network

Networks:	Complete	Undirected circle	Directed circle	Directed line
Random-effects models:	(1)	(2)	(3)	(4)
Beliefs	-0.07	0.122**	-0.124	0.009
	(0.07)	(0.06)	(0.09)	(0.09)
Beliefs(t-1)	-0.013	0.038	0.091	0.189**
	(0.05)	(0.06)	(0.08)	(0.09)
Other's (mean) appropriation (t-1)	0.063	0.005	0.056	0.01
	(0.07)	(0.07)	(0.06)	(0.07)
Appropriation (t-1)	0.363***	0.280***	0.494***	0.516***
	(0.07)	(0.07)	(0.06)	(0.07)
Node degree = 2				-0.642
				(0.69)
Sex = 1, 1	-0.7	-0.017	-0.608	-1.264*
	(0.56)	(0.63)	(0.71)	(0.75)
Experience	0.394	0.072	0.112	-0.498
	(0.33)	(0.39)	(0.31)	(0.38)
Economics = 1	0.384	-1.079*	-0.037	-0.223
	(0.60)	(0.56)	(0.95)	(0.75)
Constant	9.193***	8.381***	8.364***	6.949***
	(1.35)	(2.14)	(1.60)	(2.18)
Observations	786	469	525	551
Number of subject	60	36	40	42
Session dummies	Yes	Yes	Yes	Yes
Round dummies	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes

Notes: Robust standard errors are clustered at the subject level, and *** p<0.01, ** p<0.05, * p<0.1. The Complete network is the omitted category.

Table F.4: Completeness: Complete network versus Undirected circle

Outcomes:	Appropriation	Appropriation	Received punishment	Punishment severity	Beliefs	Beliefs	Payoffs
Random-effects models	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Incompleteness = 1, Undirected circle	-1.384	-1.032	-5.291**	-0.149	-0.693	-0.287	23.992***
	(0.98)	(0.64)	(2.19)	(0.97)	(0.73)	(0.40)	(4.63)
Beliefs about other's appropriation		-0.011					
		(0.06)					
Appropriation (t-1)		0.362***					
		(0.05)					
Beliefs (t-1)		0.005				0.505***	
		(0.04)				(0.05)	
Received punishment (t-1)		-0.013**					
		(0.01)					
Other's (mean) appropriation (t-1)						0.018	
						(0.03)	
Sex = 2, Female	-0.367	-0.28	-0.448	-0.141	-0.568	-0.309	2.787
	(0.61)	(0.40)	(1.47)	(0.55)	(0.57)	(0.31)	(3.26)
Experience	0.335	0.182	-1.206	-0.46	0.285	0.169	2.939
	(0.39)	(0.26)	(0.88)	(0.32)	(0.38)	(0.21)	(1.85)
Economics = 1, Yes	-0.167	-0.207	-3.692*	-1.337**	1.964***	0.975***	3.712
	(0.57)	(0.36)	(1.91)	(0.67)	(0.55)	(0.28)	(4.19)
Constant	11.883***	10.137***	13.427***	4.436***	9.972***	5.891***	188.477***
	(1.11)	(1.14)	(2.02)	(0.72)	(0.81)	(0.82)	(6.96)
Observations	1,440	1,344	1,440	1,440	1,440	1,255	1,440
Number of subject	96	96	96	96	96	96	96
Session dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Round dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors are clustered at the subject level, and *** p<0.01, ** p<0.05, * p<0.1. The Complete network is the omitted category. The Complete network is the omitted category.

Table F.5: Directedness: Undirected circle versus Directed circle

Outcomes:	Appropriation	Appropriation	Received punishment	Punishment severity	Beliefs	Beliefs	Payoffs
Random-effects models:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Directedness = 1, Directed circle	0.718	0.37	-7.183***	-2.231*	-1.176	-0.553	1.348
	(1.12)	(0.63)	(2.01)	(1.35)	(0.75)	(0.37)	(4.83)
Beliefs		-0.014					
		(0.05)					
Appropriation (t-1)		0.437***					
		(0.05)					
Beliefs (t-1)		0.033				0.505***	
		(0.05)				(0.04)	
Received punishment (t-1)		-0.031***					
		(0.01)					
Other's (mean) appropriation (t-1)						0.01	
						(0.03)	
Sex = 2, Female	-0.573	-0.203	0.968	0.91	0.464	0.247	-4.932*
	(0.77)	(0.46)	(1.05)	(0.66)	(0.49)	(0.26)	(2.94)
Experience	-0.166	0.043	-0.297	-0.065	-0.949***	-0.534***	-0.815
	(0.39)	(0.24)	(0.62)	(0.49)	(0.36)	(0.19)	(1.53)
Economics = 1, Yes	-0.576	-0.369	-0.59	-0.157	0.69	0.379	0.072
	(1.13)	(0.61)	(0.87)	(0.66)	(0.58)	(0.32)	(3.83)
Constant	10.927***	8.609***	8.693***	4.033***	10.275***	6.324***	215.231***
	(1.29)	(1.21)	(2.19)	(1.40)	(0.90)	(0.80)	(6.76)
Observations	1,140	1,064	1,140	1,140	1,140	994	1,140
Number of subject	76	76	76	76	76	76	76
Session dummies	yes	yes	yes	yes	yes	yes	yes
Round dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors are clustered at the subject level, and *** p<0.01, ** p<0.05, * p<0.1. The Complete network is the omitted category. The Complete network and period 1 (rounds 1-5) are the omitted categories.

Table F.6: Connectedness: Directed circle versus Directed line

Outcomes:	Appropriation	Appropriation	Received punishment	Beliefs	Beliefs	Payoffs
Random-effects models:	(1)	(2)	(3)	(4)	(5)	(6)
Disconnectedness = 1, Directed line	-0.956	-0.305	1.729*	-1.816**	-0.967**	2.851
	(1.30)	(0.65)	(1.02)	(0.82)	(0.41)	(4.65)
Beliefs		-0.044				
		(0.07)				
Appropriation (t-1)		0.531***				
		(0.05)				
Beliefs (t-1)		0.160**			0.535***	
		(0.06)			(0.04)	
Received punishment (t-1)		-0.02				
		(0.01)				
Other's (mean) appropriation (t-1)					0.047	
					(0.03)	
Sex = 2, Female	-1.613*	-0.749*	1.047*	0.027	-0.023	-2.985
	(0.84)	(0.44)	(0.60)	(0.54)	(0.27)	(2.94)
Experience	-0.745*	-0.104	-0.053	-1.035***	-0.541***	-3.352*
	(0.44)	(0.23)	(0.40)	(0.34)	(0.16)	(1.96)
Economics = 1, Yes	0.36	0.01	-0.05	0.781	0.382	7.875**
	(1.14)	(0.55)	(0.69)	(0.68)	(0.32)	(3.94)
Constant	13.146***	6.935***	1.776*	11.126***	5.989***	213.975***
	(1.12)	(1.07)	(1.08)	(0.90)	(0.91)	(6.41)
Observations	1,440	1,148	1,230	1,440	1,258	1,440
Number of subject	96	82	82	96	96	96
Session dummies	yes	yes	yes	yes	yes	yes
Round dummies	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors are clustered at the subject level, and *** p<0.01, ** p<0.05, * p<0.1. The Complete network is the omitted category. The Directed circle network is the omitted category.

Table F.7: Nodes in Complete network: N033

Outcomes:	Appropriation	Appropriation	Received punishment	Beliefs	Beliefs	Payoffs
Random-effects models:	(1)	(2)	(3)	(4)	(5)	(6)
Node label = 2, B	1.822	1.315*	1.224	-1.898	-0.967	6.118
	(1.29)	(0.80)	(2.52)	(1.30)	(0.80)	(5.88)
Node label = 3, C	-0.439	-0.191	-1.518	-0.19	0.058	0.124
	(1.23)	(0.81)	(2.51)	(1.19)	(0.71)	(5.94)
Node label = 4, D	0.748	0.639	2.392	0.899	0.466	8.426
	(1.13)	(0.75)	(2.18)	(1.12)	(0.67)	(5.75)
Beliefs		-0.052				
		(0.07)				
Appropriation (t-1)		0.350***				
		(0.07)				
Beliefs (t-1)		-0.003			0.449***	
		(0.05)			(0.06)	
Received punishment (t-1)		-0.011				
		(0.01)				
Other's (mean) appropriation (t-1)					0.017	
					(0.04)	
Sex	-0.865	-0.705	1.094	-1.078	-0.658*	5.404
	(0.84)	(0.53)	(1.51)	(0.68)	(0.40)	(4.66)
Experience	0.673	0.427	0.144	0.782**	0.453***	3.609
	(0.49)	(0.32)	(1.02)	(0.31)	(0.17)	(2.68)
Economics	0.423	0.204	-3.372*	1.991***	1.098**	9.596*
	(0.98)	(0.65)	(1.85)	(0.77)	(0.44)	(5.14)
Constant	10.508***	9.714***	1.512	9.130***	6.165***	199.578***
	(1.59)	(1.37)	(2.77)	(1.52)	(1.33)	(9.93)
Observations	900	840	900	900	786	900
Number of subject	60	60	60	60	60	60
Session dummies	Yes	Yes	Yes	Yes	Yes	Yes
Round dummies	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors are clustered at the subject level, and *** p<0.01, ** p<0.05, * p<0.1. Node label A is the omitted category.

Table F.8: Nodes in Undirected circle network: N122

Outcomes:	Appropriation	Appropriation	Received punishment	Beliefs	Beliefs	Payoffs
Random-effects models:	(1)	(2)	(3)	(4)	(5)	(6)
Node label = 1, A	-3.082**	-2.105**	-1.497	-0.331	-0.17	-18.804***
	(1.44)	(0.98)	(2.88)	(1.05)	(0.54)	(4.48)
Node label = 2, B	-0.691	-0.33	-2.869	0.429	0.365	-2.147
	(1.46)	(1.07)	(2.70)	(1.04)	(0.54)	(4.09)
Node label = 3, C	-0.311	-0.161	-0.136	0.924	0.493	-1.459
	(1.35)	(0.94)	(3.04)	(1.17)	(0.63)	(4.30)
Beliefs		0.096				
		(0.06)				
Appropriation (t-1)		0.279***				
		(0.07)				
Beliefs (t-1)		0.023			0.508***	
		(0.06)			(0.06)	
Received punishment (t-1)		-0.011				
		(0.02)				
Other's (mean) appropriation (t-1)					0.008	
					(0.05)	
Sex	0.151	0.116	0.44	0.17	0.01	-2.131
	(0.90)	(0.65)	(1.79)	(0.70)	(0.37)	(3.10)
Experience	-0.548	-0.217	-1.066	-0.802	-0.43	-0.87
	(0.54)	(0.37)	(1.19)	(0.65)	(0.35)	(2.64)
Economics	-0.304	-0.364	-0.902	1.894**	0.935*	0.688
	(0.96)	(0.65)	(1.59)	(0.75)	(0.48)	(5.07)
Constant	12.379***	9.891***	9.702***	9.973***	6.223***	221.387***
	(1.87)	(1.97)	(3.29)	(1.58)	(1.12)	(6.77)
Observations	540	504	540	540	469	540
Number of subject	36	36	36	36	36	36
Session dummies	Yes	Yes	Yes	Yes	Yes	Yes
Round dummies	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors are clustered at the subject level, and *** p<0.01, ** p<0.05, * p<0.1. Node label D is the omitted category.

Table F.9: Nodes in Directed circle network: N211

Outcomes: Random-effects models:	Appropriation (1)	Appropriation (2)	Received punishment (3)	Beliefs (4)	Beliefs (5)	Payoffs (6)
Node label = 2, B	1.002	0.542	0.45	-0.374	-0.234	2.38
	(1.36)	(0.70)	(0.90)	(0.84)	(0.40)	(5.68)
Node label = 3, C	-0.894	-0.539	2.334	-0.284	-0.222	-9.710***
	(1.35)	(0.72)	(2.22)	(0.69)	(0.37)	(3.35)
Node label = 4, D	-0.249	0.19	2.518*	-0.344	-0.17	-6.435
	(1.42)	(0.73)	(1.40)	(1.01)	(0.54)	(5.00)
Beliefs		-0.11				
		(0.09)				
Appropriation (t-1)		0.498***				
		(0.05)				
Beliefs (t-1)		0.062			0.491***	
		(0.08)			(0.06)	
Received punishment (t-1)		-0.030**				
		(0.01)				
Sex	-1.113	-0.33	1.904*	0.604	0.427	-6.342
	(1.38)	(0.73)	(0.99)	(0.64)	(0.29)	(4.71)
Experience	0.116	0.13	-0.106	-1.082***	-0.646***	-0.234
	(0.53)	(0.30)	(0.64)	(0.41)	(0.23)	(1.58)
Economics	-0.253	-0.236	0.763	-0.014	0.058	2.913
	(1.81)	(0.87)	(0.83)	(0.85)	(0.41)	(4.97)
Other's (mean) appropriation (t-1)					0.011	
					(0.05)	
Constant	11.642***	9.034***	-0.231	11.418***	6.974***	217.284***
	(1.75)	(1.31)	(1.97)	(1.19)	(1.40)	(8.83)
Observations	600	560	600	600	525	600
Number of subject	40	40	40	40	40	40
Session dummies	Yes	Yes	Yes	Yes	Yes	Yes
Round dummies	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors are clustered at the subject level, and *** p<0.01, ** p<0.05, * p<0.1. Node label A is the omitted category.

Table F.10: Nodes in Directed line network

Outcomes: Random-effects models:	Appropriation (1)	Appropriation (2)	Received punishment (3)	Beliefs (4)	Beliefs (5)	Payoffs (6)
Node label = 2, B (N311)	2.316*			1.049	0.562	6.418
	(1.27)			(0.95)	(0.48)	(6.17)
Node label = 3, C (N311)	-0.313	-1.011	-0.092	-1.108	-0.537	-11.525*
	(1.82)	(0.95)	(0.96)	(1.13)	(0.57)	(6.21)
Node label = 4, D (N301)	-0.507	-1.167	-1.768*	-1.974**	-0.804	-3.886
	(1.49)	(0.71)	(0.92)	(1.00)	(0.55)	(6.17)
Beliefs		-0.015				
		(0.09)				
Appropriation (t-1)		0.514***				
		(0.08)				
Beliefs (t-1)		0.189**			0.527***	
		(0.08)			(0.05)	
Received punishment (t-1)		-0.01				
		(0.02)				
Other's (mean) appropriation (t-1)					0.069	
					(0.05)	
Sex	-2.717**	-1.409*	-0.414	-1.207	-0.676	-3.943
	(1.33)	(0.75)	(0.91)	(0.86)	(0.47)	(4.88)
Experience	-1.354**	-0.426	-0.299	-0.950**	-0.460**	-4.289
	(0.63)	(0.35)	(0.38)	(0.46)	(0.23)	(3.00)
Economics	0.834	0.111	-1.263	1.564	0.741	13.925***
	(1.40)	(0.76)	(0.88)	(1.00)	(0.48)	(4.93)
Constant	14.659***	8.056***	3.534**	13.573***	7.365***	212.207***
	(2.14)	(1.88)	(1.65)	(1.45)	(1.37)	(11.45)
Observations	840	588	630	840	733	840
Number of subject	56	42	42	56	56	56
Session dummies	Yes	Yes	Yes	Yes	Yes	Yes
Round dummies	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors are clustered at the subject level, and *** p<0.01, ** p<0.05, * p<0.1. Node label A is the omitted category.

Table F.11: Received punishment: Pooled sample

Regression models: Pooled sample	Random Effects (1)	Probit (2)
Treatment = 1, Undirected circle	3.557*	0.544***
	(1.864)	(0.131)
Treatment = 2, Directed circle	-4.511***	-0.690***
	(1.588)	(0.139)
Treatment = 3, Directed line	-2.970**	-0.243
	(1.361)	(0.166)
Positive deviation-Pareto	0.899***	0.082***
	(0.105)	(0.007)
Negative deviation-Pareto	-0.281*	-0.056***
	(0.146)	(0.019)
Stage 1 payoff	-0.013	-0.000
	(0.010)	(0.001)
Sex = 1, 1	1.626**	0.111
	(0.683)	(0.072)
Experience	-0.160	-0.056
	(0.384)	(0.040)
Economics = 1	-1.163	-0.055
	(0.748)	(0.101)
Constant	4.168	-0.645***
	(2.793)	(0.229)
Observations	2,670	2,670
Number of subject	178	178
Session + Round + Individual controls	Yes	Yes

Notes: Robust standard errors are clustered at the subject level, and *** p<0.01, ** p<0.05, * p<0.1.

Figure F.1: Predicted marginal effect of positive deviations from Pareto over Network treatment on punishment received

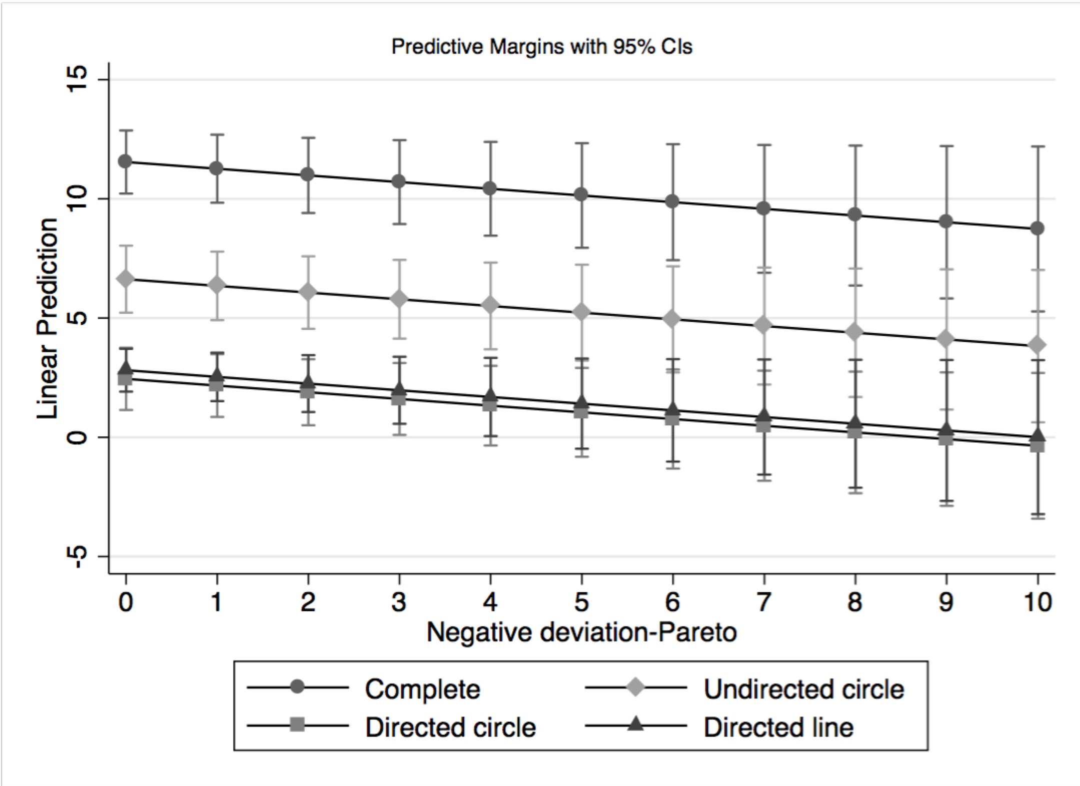


Figure F.2: Predicted marginal effect of negative deviations from Pareto over Network treatment on punishment received

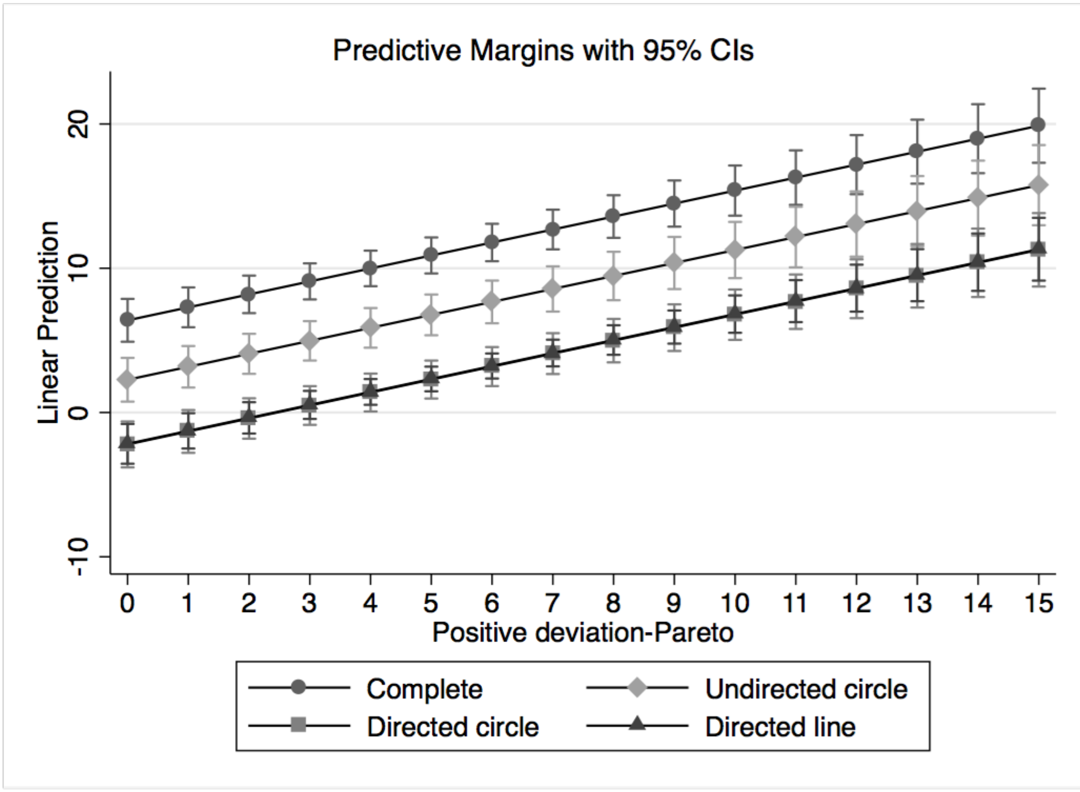


Figure F.3: Predicted marginal effect of positive deviations from Pareto over Network treatment on probability of receiving punishment

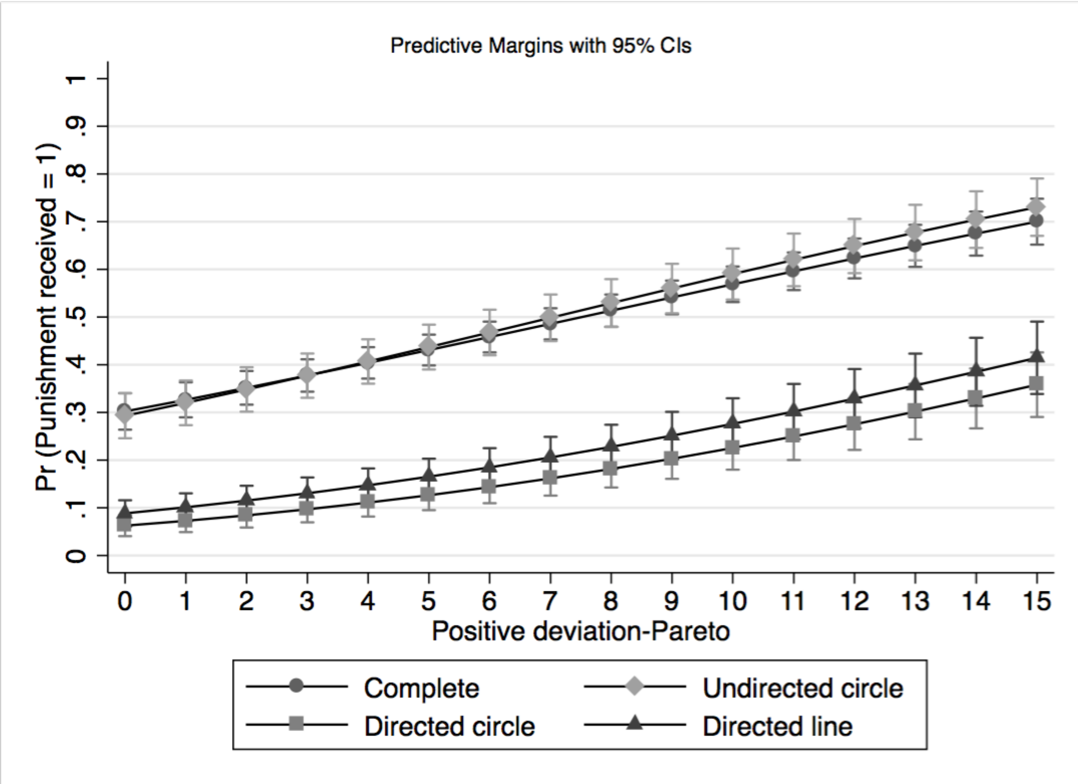


Figure F.4: Predicted marginal effect of negative deviations from Pareto over Network treatment on probability of receiving punishment

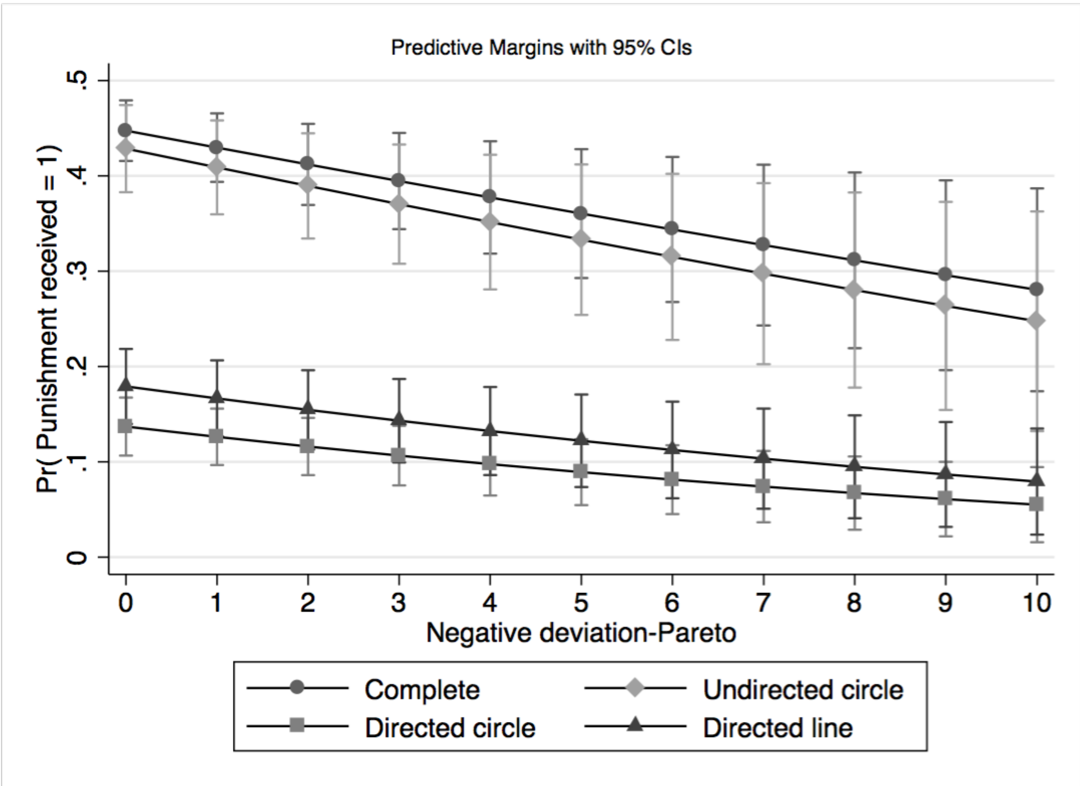


Table F.12: Deviation in beliefs and other's (mean) appropriation by networks

Outcome:	Deviation between Beliefs-Others (mean) appropriation
Random-effects model:	(1)
Treatment = 1, Undirected circle	-0.753
	(0.92)
Treatment = 2, Directed circle	0.421
	(0.88)
Treatment = 3, Directed line	1.41
	(1.10)
Period = 1, Rounds 6-10	-0.673
	(0.44)
Period = 2, Rounds 11-15	-1.293***
	(0.35)
1.treat#1.period, Undirected circle x Rounds 6-10	0.897
	(0.68)
1.treat#2.period, Undirected circle x Rounds 11-15	1.286**
	(0.64)
2.treat#1.period, Directed circle x Rounds 6-10	1.290**
	(0.60)
2.treat#2.period, Directed circle x Rounds 11-15	1.650**
	(0.66)
3.treat#1.period, Directed line x Rounds 6-10	-0.193
	(0.70)
3.treat#2.period, Directed line x Rounds 11-15	0.328
	(0.72)
Sex	0.388
	(0.42)
Experience	0.403
	(0.28)
Economics	-1.462***
	(0.44)
Constant	1.726**
	(0.79)
Observations	2,880
Number of subject	192
Session dummies	Yes
Individual controls	Yes

Notes: Robust standard errors are clustered at the subject level, and *** p<0.01, ** p<0.05, * p<0.1. The Complete network and period 1 (rounds 1-5) are the omitted categories.

Appendix G

Supplementary materials for Chapters 2 and 3

G.1 Video scripts

G.1.1 Non-charismatic species script: Giant Leaf-nosed Bat

Introduction: This is the Giant Leaf-nosed Bat. The Giant Leaf-nosed Bat lives in the Savanna, in sub-Saharan Africa. Bats live in groups, called colonies, in cave habitats but also roost in tree canopies, hollow trees and dense vegetation.

Ecological role: Bats have an important role in maintaining the health of the local ecosystem. Bats maintain the equilibrium in the Savanna ecosystem by consuming a large number of insects. They also feed on fruit and nectar, and in the process, they pollinate numerous plants and disperse seeds.

Endangerment: Although the Giant Leaf-nosed Bat was once a widespread species, the population is now in significant decline. It is classified as a Threatened species, but it has disappeared in the majority of its range. Habitat loss and conversion has led to a number of Bat populations becoming small, isolated or extinct.

Information on anthropogenic threat: *But the main threats to Bats are indiscriminate mining in limestone caves and disturbance of their roosting spots by local populations. Illegal hunting for their pelts and their meat has also lead to a population decline in some areas.*

End: The Giant Leaf-nosed Bat is one of Africa's greatest treasures, but needs protection to survive.

G.1.2 Charismatic species script: African Lions

Introduction: This is the African Lion. The African Lion lives in the Savanna, in sub-Saharan Africa. Lions live in groups, called prides, in open grasslands or woodlands.

Ecological role: Lions have an important role in maintaining the health of the local ecosystem. Lions maintain the predator-prey equilibrium in the Savanna. By hunting medium and large herbivores, lions keep their populations in check to prevent over-grazing and habitat destruction.

Endangerment: Although the African Lion was once a widespread species, the population is now in significant decline. It is classified as a Vulnerable species, but it has disappeared in the majority of its range. Habitat loss and conversion has led to a number of Lion populations becoming small, isolated or extinct.

Information on anthropogenic source of threat: *But the main threat to Lions comes from local*

populations that kill them to protect themselves and their livestock. Illegal hunting for trophies and meat has also led to a population decline in some areas.
End: The African Lion is one of Africa's greatest treasures, but needs protection to survive.

G.1.3 Complex habitat script: Bats and Lions in the African Savanna

Introduction: This is the Savanna, in sub-Saharan Africa. The African Savanna is the largest grassland and woodland ecosystem in the world and supports a wide variety of plant and animal life.
Ecological role: The diverse community of organisms that live here depend on each other to form a complex food web. The African Lion for instance has an important ecological role in the savanna. By hunting medium and large herbivores, lions keep their populations in check to prevent over-grazing and habitat destruction. The Giant Leaf-nosed Bat is another species that has an important role in maintaining local ecosystem health. By consuming large numbers of insects, bats keep their population in check. They also pollinate numerous plants and disperse seeds.
Endangerment: Although the Savanna - and its wildlife - was once widespread, this ecological habitat is now in significant decline. The African Lion, for example, is classified as Vulnerable, and has disappeared in the majority of its range. The Giant Leaf-nosed Bat is also Threatened, and missing in its native range.
Information on anthropogenic source of threat: *Intensive farming, deforestation and over-grazing have led to the removal of naturally occurring Savanna vegetation and habitats. Other threats from humans to both lions and bats are killings by local populations as well as illegal hunting for meat and body parts.*
End: The Savanna grassland and its endangered animals - such as the Lion and the Bat - are some of Africa's greatest treasures, but need protection to survive.

G.2 Video links

Bats – Control: https://youtu.be/hg28VbhLbAA
Bats – Cause: https://youtu.be/cQVT7wJ0hoQ
Lions – Control: https://youtu.be/k-KVGQSizgE
Lions – Cause: https://youtu.be/2nF_mrfsdwU
Savanna – Control: https://youtu.be/yKA60PevI9w
Savanna – Cause: https://youtu.be/AErTDRa0XaU

G.3 Sequence of photos with links

The videos are intended only for education/research purposes as in this paper. All photos were taken from Wikipedia, Wikimedia, Flickr, Google images., Search terms included Africa, Savanna, Lion, Leaf nosed bat. Images used were available under the creative commons license and/or for reuse for non-commercial purposes. Hyper-links are provided by the source name and date wherever available. No copyright infringement is intended.

G.3.1 Bats and Lions

1 Intro: "Please clear your mind of all thoughts and feelings." (20 seconds)

2 Single individual in habitat 1

  2a Bats: Frank Vassen, 2010:https://www.flickr.com/photos/42244964@N03/4315234399

  2b Lions: Kevin Pluck, 2004: https://upload.wikimedia.org/wikipedia/commons/7/73/Lion_waiting_in_Namibia.jpg

3 Savanna landscape 1: Ikiwaner, 2008: https://commons.wikimedia.org/wiki/File:Kiang_West_savanna.jpg;

4 Savanna landscape 2: CT Cooper, 2011:https://commons.wikimedia.org/wiki/File:Savanna_towards_the_north_from_Lion_Rock_in_the_LUMO_Community_Wildlife_Sanctuary,_Kenya.jpg

5 Pair of individuals

  5a Bats: Charlesjsharp, 2013: https://commons.wikimedia.org/wiki/File:Commerson%27s_leaf-nosed_bats_hipposideros_commersoni.jpg

  5b Lions: Robek, 2006: https://commons.wikimedia.org/wiki/File:Pair_of_lions.jpg

6 Single individual in habitat 2

  6a Bats: David Dennis, 2007:https://commons.wikimedia.org/wiki/File:Bat_in_a_Cave.jpg

  6b Lions: Anette Mossbacher:https://anettemossbacher.photoshelter.com/image/I0000sRSnFv.8ONg

7 Group/family in habitat 1

  7a Bats: US Geological survey 2014:https://www.flickr.com/photos/usgeologicalsurvey/14539308013/in/photolist-o9MKJn-eouGhy-87sHDx-enV1oH-8YbKC7-nw2uSV-dfZFyX-6iTy5p-dnfyQT-b

  7b Lions: Benh LIEU SONG 2012:https://commons.wikimedia.org/wiki/File:Lions_Family_Portrait_Masai_Mara.jpg

8 Group/family in habitat 2

  8a Bats: BBC 2014: http://www.bbc.co.uk/nature/life/Horseshoe_bat

  8b Lions: amanderson2: https://www.flickr.com/photos/amanderson/4685708477/in/photolist-894tTc-

9 Single individual

  9a Bats: Micheal Pennay 2009: a.%09https://commons.wikimedia.org/wiki/File:Hipposideros_diadema_(3933426171).jpg

  9b Lions: Corinata 2008: https://commons.wikimedia.org/wiki/File:Lions_hunting_Africa.jpg

10 Ecological role photo

  10a Bats with pollen: Merlin D Tuttle 2015: https://www.flickr.com/photos/usdagov/15472782607

  10b Lions eating: Samuele Cavadini, 2010: https://www.flickr.com/photos/fusion68k/2385374947

11 Single individual in habitat 3

- 11a Bats: Coke and Som Smith photography and travel: http://www.cokesmithphototravel.com/wildlife-of-sri-lanka.html
- 11b Lions: Drew Avery 2009: https://www.flickr.com/photos/33590535@N06/3527041123

12 Single individual in habitat 4

- 12a Bats: Coke and Som Smith photography and travel: http://www.cokesmithphototravel.com/wildlife-of-sri-lanka.html
- 12b Lions: freestock.ca, 2008: https://commons.wikimedia.org/wiki/File:Lion_Female_Kruger_National_Park.jpg

13 Habitat loss: deforestation/tree burning: Frank Vassen 2010: https://commons.wikimedia.org/wiki/File:Slash_and_Burn_Agriculture,_Morondava,_Madagascar.jpg

14 Deceased individual

- 14a Bats: Patricia Litton, 2012: https://www.flickr.com/photos/plitton/8001828633/in/photolist-Cfx41m-o3FWsj-AmSpoN-qSP1DT-bY57F3-xzbkL5-rKQhNp-Bkkwj9-qDeUbH-QGTawe-r2QwPH-B
- 14b Lions: Africa Geographic blog, 2014: https://africageographic.com/blog/damaraland-lion-dead/

15 Cause treatment: Illegal hunting

- 15a Bats: Stan Dalone 2007:https://commons.wikimedia.org/wiki/File:Bats_for_eating_in_Laos.jpg
- 15b Lion: accessed from Flickr, creative common license, but removed

16 Single individual in habitat 7

- 16a Bats: Frank Vassen 2010: Phttps://commons.wikimedia.org/wiki/File:Commerson%E2%80%99s_Leaf-nosed_Bat,_Tsimamampetsotsa,_Madagascar.jpg
- 16b Lions: rcrhee, 2013: https://commons.wikimedia.org/wiki/File:Amboseli_Lion_(Kenya,_Day_2).jpg

G.3.2 Savanna

1 Intro: "Please clear your mind of all thoughts and feelings." (20 seconds)

2 Savanna opening: Gossipguy 2008: https://commons.wikimedia.org/wiki/File:Upland_South_Africa_Savanna.jpg

3 Savanna landscape 1: Ikiwaner, 2008: https://commons.wikimedia.org/wiki/File:Kiang_West_savanna.jpg;

4 Savanna landscape 2: CT Cooper, 2011: https://commons.wikimedia.org/wiki/File:Savanna_towards_the_north_from_Lion_Rock_in_the_LUMO_Community_Wildlife_Sanctuary,_Kenya.jpg

5 Single individual lion in habitat

- 5a Lions: Kevin Pluck, 2004: https://upload.wikimedia.org/wikipedia/commons/7/73/Lion_waiting_in_Namibia.jpg

5b Lion's ecological role photo: Samuele Cavadini, 2010: https://www.flickr.com/photos/fusion68k/2385374947

6 Single individual bat in habitat

6a Lions: Frank Vassen, 2010: https://www.flickr.com/photos/42244964@N03/4315234399

6b Bat's ecological role photo: Merlin D Tuttle 2015: https://www.flickr.com/photos/usdagov/15472782607

7 Habitat loss, deforestation/tree burning:

7a Individual Lions: freestock.ca, 2008: https://commons.wikimedia.org/wiki/File:Lion_Female_Kruger_National_Park.jpg

7b Individual Bats: Coke and Som Smith photography and travel: http://www.cokesmithphototravel.com/wildlife-of-sri-lanka.html

8 Cause: Intensive farming, overgrazing: Hobgood, 1987 – 1991: https://commons.wikimedia.org/wiki/File:Typical_Bandundu_savanna_village.jpg

8a Deceased Lions: Africa Geographic blog, 2014: https://africageographic.com/blog/damaraland-lion-de

8b IDeceased Bats: Patricia Litton, 2012: https://www.flickr.com/photos/plitton/8001828633/in/photolist-Cfx41m-o3FWsj-AmSpoN-qSP1DT-bY57F3-xzbkL5-rKQhNp-Bkkwj9-qDeUbH-QGTawe-r2QwPI

9 Lion/Bat/Savanna collage:

9a Lions: dutchbaby 2009: http://www.cokesmithphototravel.com/wildlife-of-sri-lanka.html

9b Bats: Coke and Som Smith photography and travel: https://www.flickr.com/photos/godutchbaby/4081148859

9c Savanna: CT Cooper, 2011: https://commons.wikimedia.org/wiki/File:Savanna_towards_the_north_from_Lion_Rock_in_the_LUMO_Community_Wildlife_Sanctuary,_Kenya.jpg

G.4 Snapshots of Experimental interface

Figure G.1: Instructions for watching film

Please sit directly facing the screen. Make sure that your shoulders and head are in line with the box on either side of the walls of your cubicle. Do not put your hands on your face or lean forward into the computer.

Remain seated in this position for the rest of the session. Please put on the headphones that are on your cubicle.

Please click on the **play** button. Proceed to the next page by clicking the **'next'** button only after you have watched the entire video. Please note that some pictures maybe disturbing to some viewers.

Do not press any other button on this screen.

Figure G.2: Donation page

LSE THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

One person from this session will be given £25. You and every other person in the room has an equal and fair chance of being selected.

If you are selected, you will keep £25, minus whatever you choose to donate to the Africa Wildlife Foundation. The Africa Wildlife Foundation is a charity that works to conserve vulnerable African species, and their habitats. You can choose to donate the whole £25, a part or none of it.

To publicly acknowledge your donation, 'The Beaver', which is the newspaper of the LSE Student Union will run a short piece listing the names of the donors and the charity later this year. There will also be posters listing the names of the donors and the charity in the Saw Swee Hock Student Centre and the LSE Library.

Please enter your donation amount using the slider below.

0 25

Donation amount in Pounds (£)

Notes: Films with Bats and Lions films only have a single picture of the individual embedded in this donation appeal photo, and the size of each photo image is held constant across groups. Note that all groups have a default donation on the slider of 0. Interventions without the offer of public recognition lack the following paragraph starting with, "To publicly acknowledge your donation 'The Beaver'..."

Figure G.3: Donations receipt and further payment instructions

THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

You decided to donate £ ${q://QID141/TotalSum}.

Please write down your lab ID code and postal address on the paper form on your table. Your address will be used only to send you a receipt from the charity to acknowledge any donation amount that you may have decided to make. Do not write your name or anything else. A lab volunteer will come around to collect this shortly.

One person will be picked at random from the participants in the lab. You and every other person in the room have an equal and fair chance of being selected. The selected person will receive the £25 minus any donation amount that they may have decided to make.

Figure G.4: Affect questions

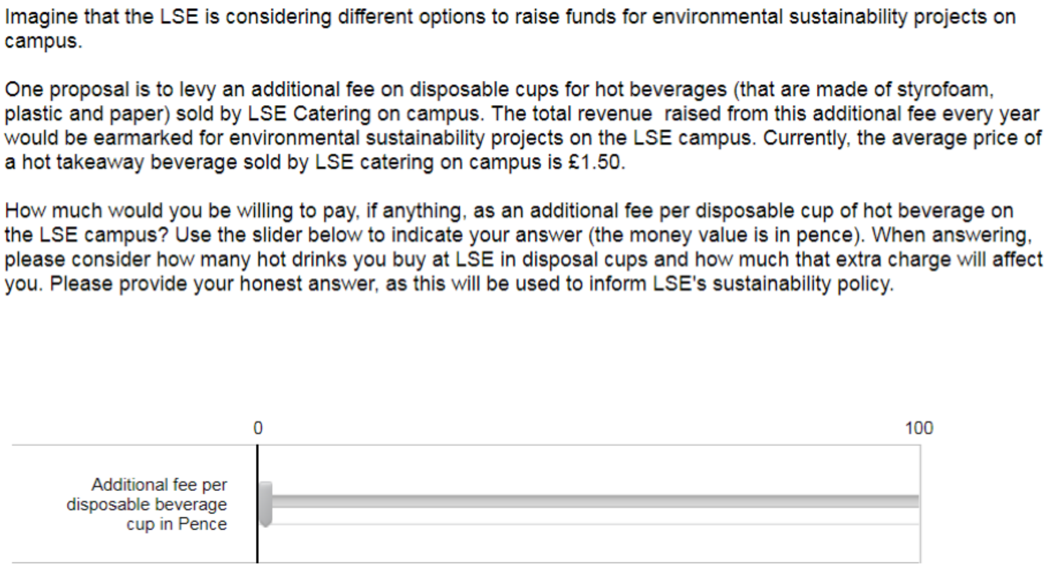
THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

This scale consists of a number of words and phrases that describe different feelings and emotions.

Please indicate to what extent you have felt this way while watching the film clip. Read each item and then select the appropriate answer .

	None at all	A little	A moderate amount	A lot	A great deal
Angry	○	○	○	○	○
Guilty	○	○	○	○	○
Sad	○	○	○	○	○
Calm	○	○	○	○	○
Sympathetic	○	○	○	○	○
Happy	○	○	○	○	○
Interested	○	○	○	○	○

Figure G.5: Willingness to Pay a green fee (WTP)



Imagine that the LSE is considering different options to raise funds for environmental sustainability projects on campus.

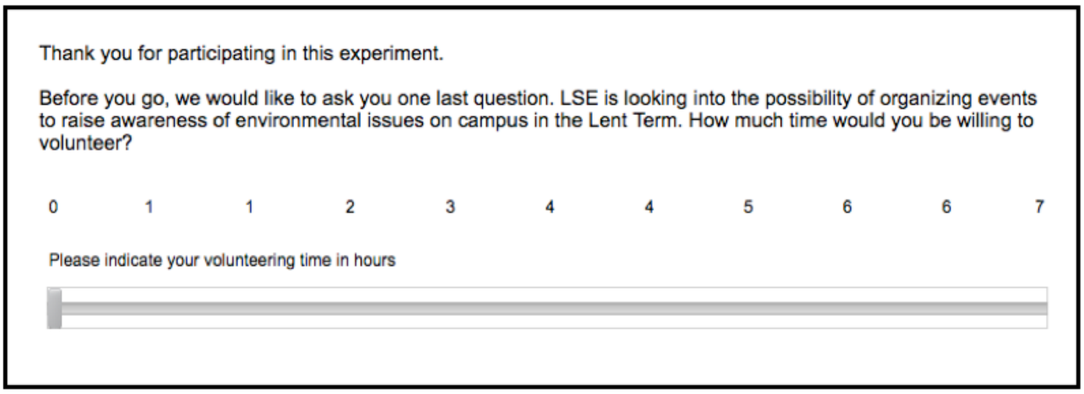
One proposal is to levy an additional fee on disposable cups for hot beverages (that are made of styrofoam, plastic and paper) sold by LSE Catering on campus. The total revenue raised from this additional fee every year would be earmarked for environmental sustainability projects on the LSE campus. Currently, the average price of a hot takeaway beverage sold by LSE catering on campus is £1.50.

How much would you be willing to pay, if anything, as an additional fee per disposable cup of hot beverage on the LSE campus? Use the slider below to indicate your answer (the money value is in pence). When answering, please consider how many hot drinks you buy at LSE in disposal cups and how much that extra charge will affect you. Please provide your honest answer, as this will be used to inform LSE's sustainability policy.

0 100

Additional fee per disposable beverage cup in Pence

Figure G.6: Willingness to Donate time (WTD)



Thank you for participating in this experiment.

Before you go, we would like to ask you one last question. LSE is looking into the possibility of organizing events to raise awareness of environmental issues on campus in the Lent Term. How much time would you be willing to volunteer?

0 1 1 2 3 4 4 5 6 6 7

Please indicate your volunteering time in hours

G.5 Debrief sheet

Study on economic decision making and social issues Thank you for participating in this experiment.

This study aims to uncover how participants respond to different types of media content of biodiversity conservation films. Specifically, the study examines if different types of species or information about the conservation issue impacts [economic decision making, through the donation] or how people feel after watching the film. First all participants watch a short movie. *[They can then decide to donate some or any part of their endowment to an organization working on wildlife conservation, if they so wish (Africa Wildlife Foundation).]* Then, they state the amount of affect (i.e. emotional states) they feel after watching the movie.

All the data from the experiment is anonymised, private and confidential. Please note that some of the photographs of the bats included photographs of different bat species, other than the Giant leaf nosed bat. This was due to the scarcity of photos for the focus species.

If subjects would like more information about the study, please contact the researcher at *email*.

Notes: Text in italics for was used in debrief form for Study 1 only.

Appendix H

Supplementary materials for Chapters 4 and 5

H.1 Instructions

H.1.1 Survey implementation

Notes on data collection: The data was collected at the Prudential Ride London Festival during 28-30 July 2017. The data collection venues were the Olympic Park and ExCel Exhibition Centre on 28 July 2017, and Green Park/The Mall. All venues attracted spectators, cyclists and their families, and had numerous cycling-themed event and merchandise stalls. The Olympic Park and ExCel Exhibition centre venues were selected because they were the only active PRL events on 28 July 2017. The Green Park/The Mall was selected for data collection during 29-30 July, because all cycling events were routed through this venue. It also had the largest festival zones for spectators. To minimise procedural variance, all surveyors were trained and undertook pilot surveys, the week prior to the survey. They all dressed identically and followed the same opening script. If the participant answered yes to three qualifying questions, she was handed the tablet with the survey open at the consent form. After agreeing to participate, subjects were shown the brief preamble to clarify the rules of the survey including answering alone and truthfully. When we consider the number of observations by location, surveyor and time of day (table B1), it is clear that the majority of responses were collected in Green Park/The Mall (164/181 observations).

Table H.1: Survey variables and balance on covariates

Variables	Category	Control group	Treatment group	Test of equality p-value	All
Location	GP/Mall	61	68	0.494	129
	ExCel centre	15	10		25
	Olympic park	14	13		27
Surveyor	Surveyor 1	7	7	0.739	14
	Surveyor 2	25	24		49
	Surveyor 3	27	34		61
	Surveyor 4	31	26		57
Time of day	Morning	26	32	0.366	58
	Afternoon	64	59		123
Sample size		90	91		181

Notes : The table presents the number of observations (share of total) collected by survey variable for the treatment and control groups. The p-value is from a chi-squared test, which tests the null hypothesis of differences in distributions in between the control and treatment groups.

Figure H.1: Opening script

Hello!

Do you cycle in London, and live in the greater London Area?

We are doing research on cycling and air pollution in the city.

You could win some money and a prize worth up to £40 for your participation.

It will take around 10 minutes.

Your answers will be recorded on a tablet.

Figure H.2: Preamble

Thank you for participating.

Please answer the questions alone and truthfully, without anyone else's input. We are only interested in what you think, and your choices.

If you have any questions or doubts, please ask the surveyor.

H.1.2 Note on risk perception

Apart from risk aversion, an individual's subjective perception of the risk associated with different choices or the risk inherent in a specific situational context, has been identified as another key dimension of risk in economics and psychology. Under the EUT framework, individuals can hold subjective risk probabilities which guide decision making when objective probabilities are unknown. In psychology, the risk-return model proposes that the perceived riskiness of a particular choice, determines attractiveness of that choice, alongside risk preference and the perceived benefit (Weber et al., 2002). It emphasizes that both risk preferences and risk perceptions are domain-specific, and that the perceived risk attached to different choices explains a significant proportion of the variability of a person's level of apparent risk taking across risk domains. An important body of work has established that risk perceptions are contingent on a variety of factors apart from cognitive processes, objective probabilities or access to information about them. These include the role of group-level socio-cultural and political factors conceptualized in the socio-cultural paradigm, and people's emotional reactions to risky situations in the psychometric paradigm (Weber, 2001; Slovic et al., 2004; Slovic and Peters, 2006). Perceived risk is also an important variable that is linked to the uptake of preventive health and pro-environmental behaviours, in the Health Belief Model (Rosenstock et al., 1988) and the Theory of Planned Behaviour (Ajzen, 1985, 1991).

The behavioural validity of risk perception has been empirically explored both in relation to health and environmental risks. Most studies find higher risk perception attached to negative outcomes (e.g. morbidity or mortality), events (e.g. climate change or accidents) or technologies (e.g. GM foods), is associated with behavioural intentions or decisions to self-protect or mitigate the risk.[1] For instance, higher risk perception has been linked to the lower acceptance and consumption of GM food (Lusk and Coble, 2005), reduction of beef consumption due to mad cow disease (Pennings et al., 2002), lower risk taking behaviour in traffic (Ulleberg and Rundmo, 2003) and speeding (Machin and Sankey, 2008), greater willingness to mitigate climate change (Leiserowitz, 2006; Spence et al., 2011, 2012), greater frequency of breast cancer screenings and the uptake of mammographies (Goldzahl, 2017; Carman and Kooreman, 2014; Katapodi et al., 2004), attempts and intentions to quit smoking (Lin and Sloan, 2015) and decisions to purchase flood insurance policy (Petrolia et al., 2013). Psychological studies note the 'white male' effect in risk perception research, i.e., the tendency for a larger proportion of white men tend to judge risks as lower compared to women and minority ethnic groups (Finucane et al., 2000; Kahan et al., 2007; Whitmarsh, 2011; Kahan et al., 2011).

Risk perception has also been measured using experimental and questionnaire methods. Experimental and incentive-compatible methods are most commonly used in the economics literature to elicit rankings of mortality (or environmental) risk (e.g. in Harrison and Rutström (2006) or through scoring rules (Andersen et al., 2014). Questionnaire methods can be further divided into three (broad) types of risk perception measures and their corresponding theoretical foundations. The first pertains to hypothetical survey questions asking subjects to rank the probability of different contracting risks or various diseases (similar to experimental methods; e.g.).[2] Secondly, the DOSPERT scale elicits the perceived riskiness of different actions (perceived risk and benefit), as previously discussed. Thirdly, subjects rate the subjective

[1] In the related environmental and health valuation literature, the perceived risk of contracting diseases or environmental hazards is also measured. To illustrate, Gerking et al. (2014), measure perceptions of morbidity and mortality risk from skin cancer and leukaemia, to recover willingness to pay to reduce the risk and the value of statistical life.

[2] Weber (2001) call this the axiomatic measurement paradigm, as it subjectively transform objective risk information (i.e., possible consequences of risky choice options such as mortality rates or financial losses and their likelihood of occurrence.

concern, seriousness or severity a particular risk is to themselves (and/or their loved ones) using either multi-item (e.g. in Lusk and Coble (2005)) or single-item survey questions (e.g. in Kahan et al. (2012)).

Bibliography

Ajzen, I. (1985). From intentions to actions: A theory of planned behavior. In *Action control*, pages 11–39. Springer.

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, 50(2):179–211.

Andersen, S., Fountain, J., Harrison, G. W., and Rutström, E. E. (2014). Estimating subjective probabilities. *Journal of Risk and Uncertainty*, 48(3):207–229.

Carman, K. G. and Kooreman, P. (2014). Probability perceptions and preventive health care. *Journal of Risk and Uncertainty*, 49(1):43–71.

Finucane, M. L., Slovic, P., Mertz, C. K., Flynn, J., and Satterfield, T. A. (2000). Gender, race, and perceived risk: The'white male'effect. *Health, risk & society*, 2(2):159–172.

Gerking, S., Dickie, M., and Veronesi, M. (2014). Valuation of human health: An integrated model of willingness to pay for mortality and morbidity risk reductions. *Journal of Environmental Economics and Management*, 68(1):20–45.

Goldzahl, L. (2017). Contributions of risk preference, time orientation and perceptions to breast cancer screening regularity. *Social Science & Medicine*, 185:147–157.

Harrison, G. W. and Rutström, E. E. (2006). Eliciting subjective beliefs about mortality risk orderings. *Environmental and Resource Economics*, 33(3):325–346.

Kahan, D. M., Braman, D., Gastil, J., Slovic, P., and Mertz, C. (2007). Culture and identity-protective cognition: Explaining the white-male effect in risk perception. *Journal of Empirical Legal Studies*, 4(3):465–505.

Kahan, D. M., Jenkins-Smith, H., and Braman, D. (2011). Cultural cognition of scientific consensus. *Journal of Risk Research*, 14(2):147–174.

Kahan, D. M., Peters, E., Wittlin, M., Slovic, P., Ouellette, L. L., Braman, D., and Mandel, G. (2012). The polarizing impact of science literacy and numeracy on perceived climate change risks. *Nature climate change*, 2(10):732.

Katapodi, M. C., Lee, K. A., Facione, N. C., and Dodd, M. J. (2004). Predictors of perceived breast cancer risk and the relation between perceived risk and breast cancer screening: a meta-analytic review. *Preventive medicine*, 38(4):388–402.

Leiserowitz, A. (2006). Climate change risk perception and policy preferences: The role of affect, imagery, and values. *Climatic change*, 77(1-2):45–72.

Lin, W. and Sloan, F. (2015). Risk perceptions and smoking decisions of adult chinese men. *Journal of health economics*, 39:60–73.

Lusk, J. L. and Coble, K. H. (2005). Risk perceptions, risk preference, and acceptance of risky food. *American Journal of Agricultural Economics*, 87(2):393–405.

Machin, M. A. and Sankey, K. S. (2008). Relationships between young drivers' personality characteristics, risk perceptions, and driving behaviour. *Accident analysis & prevention*, 40(2):541–547.

Pennings, J. M., Wansink, B., and Meulenberg, M. T. (2002). A note on modeling consumer reactions to a crisis: The case of the mad cow disease. *International Journal of research in marketing*, 19(1):91–100.

Petrolia, D. R., Landry, C. E., and Coble, K. H. (2013). Risk preferences, risk perceptions, and flood insurance. *Land Economics*, 89(2):227–245.

Rosenstock, I. M., Strecher, V. J., and Becker, M. H. (1988). Social learning theory and the health belief model. *Health education quarterly*, 15(2):175–183.

Slovic, P., Finucane, M. L., Peters, E., and MacGregor, D. G. (2004). Risk as analysis and risk as feelings: Some thoughts about affect, reason, risk, and rationality. *Risk analysis*, 24(2):311–322.

Slovic, P. and Peters, E. (2006). Risk perception and affect. *Current directions in psychological science*, 15(6):322–325.

Spence, A., Poortinga, W., Butler, C., and Pidgeon, N. F. (2011). Perceptions of climate change and willingness to save energy related to flood experience. *Nature climate change*, 1(1):46.

Spence, A., Poortinga, W., and Pidgeon, N. (2012). The psychological distance of climate change. *Risk analysis*, 32(6):957–972.

Ulleberg, P. and Rundmo, T. (2003). Personality, attitudes and risk perception as predictors of risky driving behaviour among young drivers. *Safety science*, 41(5):427–443.

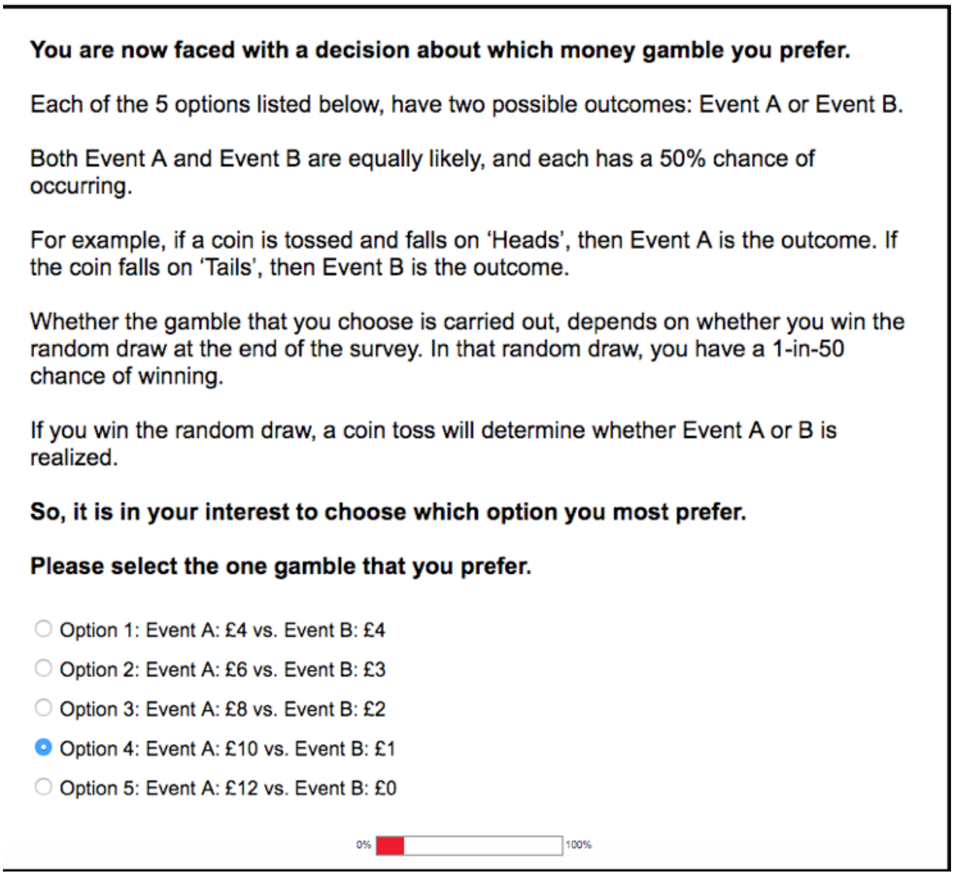
Weber, E. U. (2001). Decision and choice Risk, empirical studies. In Smelser, N. J., Baltes, P. B., et al., editors, *International encyclopedia of the social & behavioral sciences*, volume 11. Elsevier Amsterdam.

Weber, E. U., Blais, A.-R., and Betz, N. E. (2002). A domain-specific risk-attitude scale: Measuring risk perceptions and risk behaviors. *Journal of behavioral decision making*, 15(4):263–290.

Whitmarsh, L. (2011). Scepticism and uncertainty about climate change: Dimensions, determinants and change over time. *Global environmental change*, 21(2):690–700.

H.1.3 Survey questions and variables

Figure H.3: Binswanger-Eckel-Grossman (BEG) risk measure question



You are now faced with a decision about which money gamble you prefer.

Each of the 5 options listed below, have two possible outcomes: Event A or Event B.

Both Event A and Event B are equally likely, and each has a 50% chance of occurring.

For example, if a coin is tossed and falls on 'Heads', then Event A is the outcome. If the coin falls on 'Tails', then Event B is the outcome.

Whether the gamble that you choose is carried out, depends on whether you win the random draw at the end of the survey. In that random draw, you have a 1-in-50 chance of winning.

If you win the random draw, a coin toss will determine whether Event A or B is realized.

So, it is in your interest to choose which option you most prefer.

Please select the one gamble that you prefer.

- Option 1: Event A: £4 vs. Event B: £4
- Option 2: Event A: £6 vs. Event B: £3
- Option 3: Event A: £8 vs. Event B: £2
- Option 4: Event A: £10 vs. Event B: £1
- Option 5: Event A: £12 vs. Event B: £0

0% 100%

Figure H.4: Socio-Economic Panel-General (SOEP-G) risk measure question

Are you generally a person who is willing to take risks, or do you try to avoid taking risks?

Please answer on a scale from 0 to 10, where:

0 means "I am generally unwilling to take risks" and
10 means "I am generally a person, fully prepared to take risks".

Unwilling to take risk										Fully prepared to take risk
0	1	2	3	4	5	6	7	8	9	10

Figure H.5: Socio-Economic Panel-Health (SOEP-H) risk measure question

Are you generally a person who is willing to take risks, or do you try to avoid taking risks **in health**?

Please answer on a scale from 0 to 10, where:

0 means "I am generally unwilling to take risks **in health**" and
10 means "I am generally a person, fully prepared to take risks **in health**".

Unwilling to take risk										Fully prepared to take risk
0	1	2	3	4	5	6	7	8	9	10

Figure H.6: Importance of items in safety kit question

How much risk, if at all, do you think air pollution poses to your health and safety?

No risk at all										Extreme amount of risk
0	1	2	3	4	5	6	7	8	9	10

Figure H.7: Air Pollution Risk Perception (APRP) question

What do you think are essential to a cycling kit?

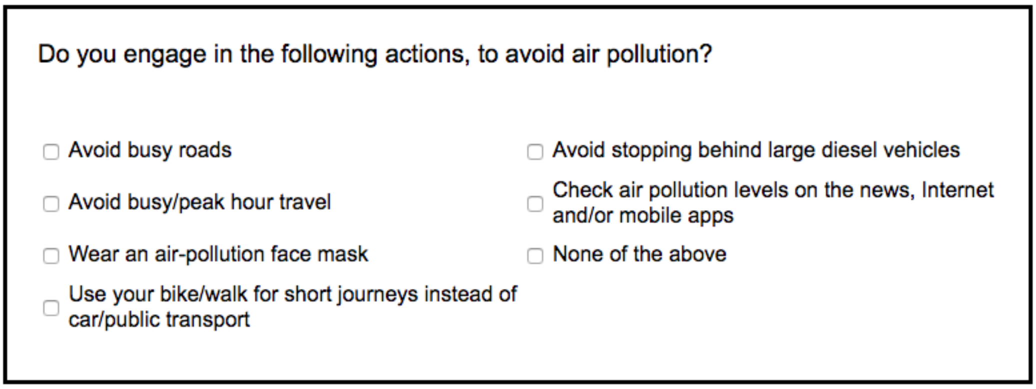
	Not at all important	Slightly important	Moderately important	Very important	Extremely important
Hi-vis gear / lights					
Helmet					
Anti-pollution face mask					

Figure H.8: Risk-taking behaviours while cycling question

While cycling, how often, if ever, do you do any of the following?

	Never	Sometimes	About half the time	Most of the time	Always
Cycle through red lights.					
Cycle with music in earphones.					
Cycle after dark without lights.					
Cycle while using a mobile phone.					
Cycle without a helmet.					
Cycle after drinking alcohol.					

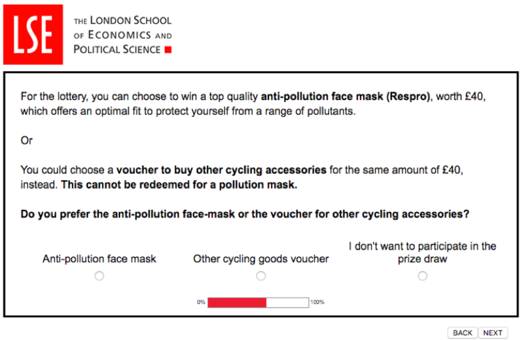
Figure H.9: Air pollution avoidance behaviours question



Do you engage in the following actions, to avoid air pollution?

- Avoid busy roads
- Avoid busy/peak hour travel
- Wear an air-pollution face mask
- Use your bike/walk for short journeys instead of car/public transport
- Avoid stopping behind large diesel vehicles
- Check air pollution levels on the news, Internet and/or mobile apps
- None of the above

Figure H.10: Facemask choice question



THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

For the lottery, you can choose to win a top quality **anti-pollution face mask (Respro)**, worth £40, which offers an optimal fit to protect yourself from a range of pollutants.

Or

You could choose a **voucher to buy other cycling accessories** for the same amount of £40, instead. **This cannot be redeemed for a pollution mask.**

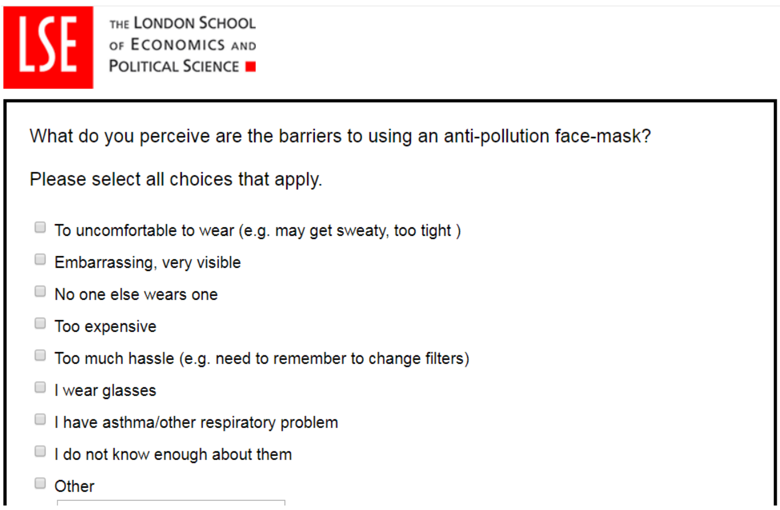
Do you prefer the anti-pollution face-mask or the voucher for other cycling accessories?

Anti-pollution face mask | Other cycling goods voucher | I don't want to participate in the prize draw

0% 100%

BACK NEXT

Figure H.11: Barreriers to facemask question



THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

What do you perceive are the barriers to using an anti-pollution face-mask?

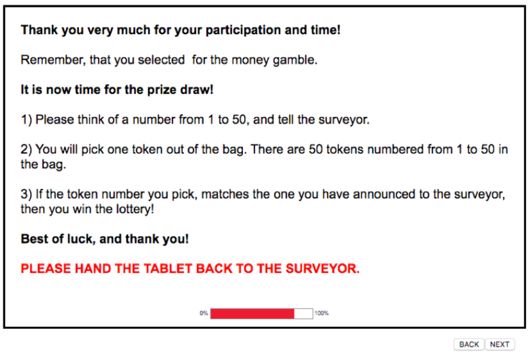
Please select all choices that apply.

- To uncomfortable to wear (e.g. may get sweaty, too tight)
- Embarrassing, very visible
- No one else wears one
- Too expensive
- Too much hassle (e.g. need to remember to change filters)
- I wear glasses
- I have asthma/other respiratory problem
- I do not know enough about them
- Other

Notes on survey questions:

Risk questions BEG risk measure is obtained from Crosetto and Filippin (2016). The SOEP-G and SOEP-H questions are obtained from the German Socio-Economic Panel survey. To measure attitudes to items in the cycling kit, a separate question (from figure H.6) id modified from previous studies such as XXX. To measure air pollution risk perception, a single item response following Kahan et al. (2016) study on Climate Change risk perception is used, as is presented to subjects on a separate screen (figure H.7).

Figure H.12: Prize draw instructions



Air pollution knowledge: Subjects also answered two questions that measured their prior knowledge about air pollution. Variants of these questions are commonly used in studies on interpersonal comparisons of knowledge of air pollution and climate change (e.g. Leiserowitz et al., 2010, DEFRA 2011). An aggregate air pollution knowledge score is constructed by adding up the points to both questions, where the minimum score is 0 and the maximum score is 5. I randomize the question order, as well as the order of the answer choices for each question, to mitigate any ordering effects. The two questions are as follows: *Air pollution knowledge- question 1*: Subjects were asked *'Which of the following cause air pollution in cities? Please select all that apply.'*, and options include Oxygen (O_2), Hydrogen (H), Nitrogen dioxide (NO_2), lead and heavy metals, Carbon monoxide (CO), particulate matter (PM 2.5, PM 10) and Don't know. The four correct answers are NO_2, lead and heavy metals, CO and particulate matter. Each correct answer earns one point. *Air pollution knowledge- question 1*: Subjects were asked *'Which of the following do you think contributes most to air pollution in London? Please choose one.'* Subjects get an additional point for the correct answer, which is 'Vehicle emissions'.

Question order: Subjects were first exposed to risk questions, followed by questions on cycling, and then air pollution. Within each survey module, the order of the questions (and items within each question if relevant) was randomized.

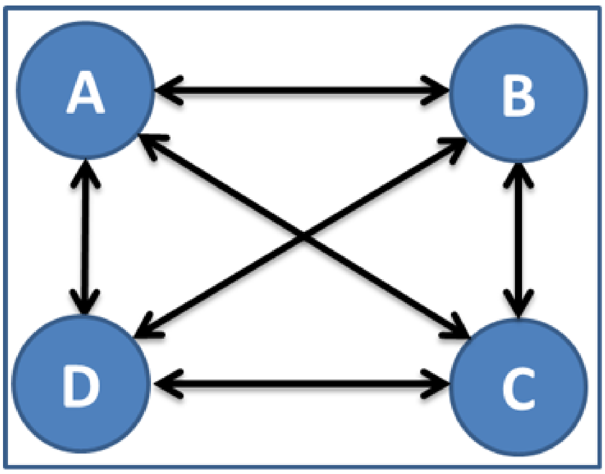
Appendix I

Supplementary materials for Chapter 6

I.1 Instructions

Instructions:
This is a study on economic decision making. If you read the following instructions carefully, you can, depending on your decisions and on the decisions of the other participants in the experiment, earn money. All earnings on your computer screen are in experimental tokens. Experimental tokens will be converted to real Great Britain Pounds (GBP) at the end of the experiment at the rate of 25 experimental tokens = GBP 1.

Introduction
In this experiment, you will participate in 15 identical decision-making periods. Each period consists of two decision stages (Stage 1 and 2) which will be described in detail below. Before the first period, you (and all other participants) will be assigned by the computer to one of the four types labelled A, B, C or D. This assignment depends solely upon chance. Each network contains one Type-A player, one Type B player, one Type C player and one Type-D player. There are an equal number of participants of Type-A, Type-B, Type-C and Type-D in the room. Everyone's type will remain the same throughout all 15 periods of the experiment.



The relationship between types is illustrated below. Type-A can observe Type-B, Type-C and Type-D, Type-B can observe Type-C, Type-D and Type-A, Type-C can observe Type-D, Type-A and Type-B, and Type-D can observe Type-A, Type-B and Type-C. When you enter Stage 1 you will be informed of your type in the dialog box on the top of the screen along with a picture of this network.

Every period begins with the computer assigning you to a four-person network or group (yourself and three other participants). Remember that each network contains one Type-A player, one Type B player, one Type C player and one Type-D player. Everyone's type will remain the same throughout all 15 periods of the experiment. In every period one participant of each type is equally likely to be chosen to be in a particular group. The network or group formed in each period depends solely upon chance and does not depend on groups formed in previous periods.

Stage 1

In Stage 1 of every period, you receive an endowment of 25 experimental tokens. You will decide to place your tokens in either or both of two accounts: a Private Account and a Common Account. The total number of tokens you place in either or both accounts must add up to your endowment of 25 tokens. Your total earnings from Stage 1 (for each period) are the sum of your returns from the Private Account and Common Account. Everyone has to make the decision at this stage and has the same returns.

Earnings from your Private Account: For each token you place in the Private Account you generate a return of 5 tokens. Your earnings from the Private Account depend only on the number of tokens you place in your private account and generate a return only to you.

Earnings from the Common Account: Each token placed in the Common Account generates a return that depends on the total number of tokens invested in the common account by all members in your group (including you) and your share of the total tokens placed in the common account in that period.

Assume a total of X tokens are placed in the Common Account by all your group members (including you). The return to your entire group from the Common Account is $25X - 0.25X^2$ tokens.

For instance, assume a total of **X=4** tokens are placed in the Common Account by all your group members (including you). The earnings to your whole group from the common account are;

$25 * (4) - 0.25 * (4)^2 = 96 \; tokens$

Your share of this total group return equals the number of tokens you placed in the Common Account divided by the total tokens placed in the Common Account by your group (Tokens you place in Common Account/X).

Following on from the example above, assume you placed 1 token in the Common Account. Then your share of the total Common Account earnings is 1/4 and your earnings from the Common Account are:

$(1/4) * 96 = 24 \; tokens$

Thus, from stage 1 your total earnings are given by;

$$\begin{aligned} YourEarnings &= Private\ Account\ Earnings\ + Common\ Account\ Earnings \\ &= [5 * Tokens\ you\ place\ in\ Private\ Account] \\ &\quad + [\frac{(Tokens\ you\ place\ in\ Common\ Account)}{(Total\ Tokens\ in\ Common\ Account\ or X)} * (25X - 0.25X^2)] \end{aligned}$$

The earnings table attached below describes your total potential earnings (sum of Private Account and Common Account earnings; in tokens) that correspond to different token placements (in steps of five) in the Common Account by you (first row) and the three others in your group (first column). Remember, you can assign any number of tokens into your Private and Common Accounts as long as they add up to your endowment of 25 tokens. All participants use the same earnings table.

On your computer screen during Stage 1, you can calculate your expected earnings from your token allocation to your Private and Common Accounts, and your estimate of the total number of tokens allocated by the three other group members to the Common Account. Use the mouse to click on the Private and Common Account input boxes and use the keyboard to fill in the number (without decimals) of tokens between 0 and 25 that you wish to allocate to that account. Do the same for your estimate of the total number of tokens allocated by the three other group members to the Common Account.

To calculate your expected earnings based on your estimate of the other group members' Common Account token allocation, and your allocation, please press the calculate button. If you are happy with your token allocations, click Confirm and Continue to proceed to next round. If you want to revise your allocations or your estimate, please key in new values and proceed in the same way. Remember, you can only enter your estimate of the total number of tokens allocated by the three other group members to the Common Account. This is not their actual decision.

Once you press Confirm and Continue, your decisions cannot be revised. This completes Stage 1 of each period. After all members of your network or group have made their decisions, your earnings from the Stage 1 will be displayed. Please click the Continue button to proceed to the Stage 2.

Stage 2

In Stage 2, you will observe the choices made by the other participants in your network. A line between any two types represents that they are connected and the arrowhead points to the participant whose decision is observed. For instance, if you are a Type-A participant, you can observe the decisions of Type-B, Type-C and Type-D and so on. This information is given to you in the table on your computer screen. Each participant can observe only allocations of those to whom they are connected in the network.

By assigning Deduction Points, you can now decide if and by how much to reduce the earnings of the participant whose allocations you can observe. Each of the other participants will also decide if and by how much to reduce the earnings of the participant whose allocations they can observe.

You must decide by how much you wish to reduce the earnings of each of the other participants with whom you are connected, by filling in the number of Deduction Points for each of them. If you do not wish to reduce the earnings of another participant, you must enter 0. Reducing the earnings of other participants is costly to you. Assigning one deduction point to another participant reduces your earnings by 1 token. Each deduction point received by a participant reduces their earnings by 3 tokens.

$Total\ Cost\ of\ Deduction\ Points\ you\ assigned = Sum\ of\ Deduction\ Points\ assigned Total\ Cost\ of\ Deduction\ Poin$
$3 * (Sum\ of\ Deduction\ Points\ you\ received)$

After, and if you have entered deduction points, click the Calculate button to check the Total Cost of Deduction Points you assigned. If you are want to revise your decision, key in another number. To confirm your decision, press Confirm and Continue. If you cannot observe other's decisions press Confirm and Continue. This completes the Stage 2 of each period.

When a period ends, the computer will inform all participants of their total earnings and the Total Cost of Deduction Points assigned and received. Please click the Continue button to proceed to the next period, which will start with the computer forming new groups of participants in networks. Remember, 15 periods will be conducted and you will receive a new endowment of 25 tokens in each period.

Earnings

Your earnings in each period will be calculated in tokens as follows:

$$\begin{aligned} Your\ Final\ Earnings = (&Your\ Total\ Earnings\ from\ Stage\ 1) \\ &- (Total\ Cost\ of\ deduction\ points\ you\ assigned) \\ &- (Total\ Cost\ of\ deduction\ points\ received) \end{aligned}$$

This sum is positive or will be zero if it is negative. Thus, if Stage 1 earnings are reduced to below zero through cost of assigned and received deduction points, total earnings for that period will be zero.

At the end of the session, you will be given your earnings from a randomly selected round out of the 15 rounds played. Additionally, players who accurately estimate the expected allocation of each of other three payers will earn 4 tokens for each correct estimate.

Rules

1. Please remain silent until the end of the last period and then wait for further instructions.
2. Please do not talk to anyone during the experiment.
3. Please remain alert during the experiment.
4. If you have any questions, please raise your hand and we will come to you to address any doubts you may have.
5. Your participation and any information about your earnings will be kept strictly confidential.

Test Questions

1. Please write down how much to invest in your private and the common account.
2. How much should the sum of your token placement in your private and common accounts add up to?
3. How much should the sum of your token placement in your private and common accounts add up to?
4. What are your total earnings (earnings from private + earnings from common account; consult earnings table) if the three other participants place 0 in the common account?
5. If you invest 25 tokens in the Common Account and the three other participants invest a total of 75 tokens, what are your total earnings?

Table of Total Earnings (Private Accounts + Common Accounts) from Stage 1 by Tokens placed in Common Account

	Number of tokens you place in Common Account →																									
Total tokens placed by 3 other group members (without you) in Common Account		**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**
	0	125	145	164	183	201	219	236	253	269	285	300	315	329	343	356	369	381	393	404	415	425	435	444	453	461	469
	1	125	145	164	182	200	218	235	251	267	283	298	312	326	340	353	365	377	389	400	410	420	430	439	447	455	463
	2	125	144	163	181	199	216	233	249	265	280	295	309	323	336	349	361	373	384	395	405	415	424	433	441	449	456
	:																										
	5	125	144	162	179	196	213	229	244	259	274	288	301	314	327	339	350	361	372	382	391	400	409	417	424	431	438
	:																										
	10	125	142	159	175	191	206	221	235	249	262	275	287	299	310	321	331	341	350	359	367	375	382	389	395	401	406
	:																										
	15	125	141	157	172	186	200	214	227	239	251	263	274	284	294	304	313	321	329	337	344	350	356	362	367	371	375
	:																										
	20	125	140	154	168	181	194	206	218	229	240	250	260	269	278	286	294	301	308	314	320	325	330	334	338	341	344
	:																										
	25	125	139	152	164	176	188	199	209	219	229	238	246	254	262	269	275	281	287	292	296	300	304	307	309	311	313
	26	125	138	151	163	175	186	197	207	217	226	235	243	251	258	265	271	277	282	287	291	295	298	301	303	305	306
	27	125	138	151	163	174	185	196	206	215	224	233	241	248	255	262	268	273	278	283	287	290	293	296	298	299	300
	:																										
	30	125	137	149	160	171	181	191	200	209	217	225	232	239	245	251	256	261	265	269	272	275	277	279	280	281	281
	:																										
	35	125	136	147	157	166	175	184	192	199	206	213	219	224	229	234	238	241	244	247	249	250	251	252	252	251	250
	:																										
	40	125	135	144	153	161	169	176	183	189	195	200	205	209	213	216	219	221	223	224	225	225	225	224	223	221	219
	:																										
	45	125	134	142	149	156	163	169	174	179	184	188	191	194	197	199	200	201	202	202	201	200	199	197	194	191	188
	:																										
	50	125	132	139	145	151	156	161	165	169	172	175	177	179	180	181	181	181	180	179	177	175	172	169	165	161	156
	51	125	132	139	145	150	155	160	164	167	170	173	175	176	177	178	178	177	176	175	173	170	167	164	160	155	150
	52	125	132	138	144	149	154	158	162	165	168	170	172	173	174	174	174	173	172	170	168	165	162	158	154	149	144
	:																										
	55	125	131	137	142	146	150	154	157	159	161	163	164	164	164	164	163	161	159	157	154	150	146	142	137	131	125
	:																										
	60	125	130	134	138	141	144	146	148	149	150	150	150	149	148	146	144	141	138	134	130	125	120	114	108	101	94
	:																										
	65	125	129	132	134	136	138	139	139	139	139	138	136	134	132	129	125	121	117	112	106	100	94	87	79	71	63
	:																										
	70	125	127	129	130	131	131	131	130	129	127	125	122	119	115	111	106	101	95	89	82	75	67	59	50	41	31
	:																										
	73	125	127	128	128	128	128	127	125	123	121	118	114	110	106	101	95	89	83	76	68	60	52	43	33	23	13
	74	125	126	127	127	127	126	125	123	121	118	115	111	107	102	97	91	85	78	71	63	55	46	37	27	17	6
	75	125	126	127	127	126	125	124	122	119	116	113	109	104	99	94	88	81	74	67	59	50	41	32	22	11	0

I.2 Snapshots of experimental interface

Figure I.1: Page 1: Appropriation decision and beliefs

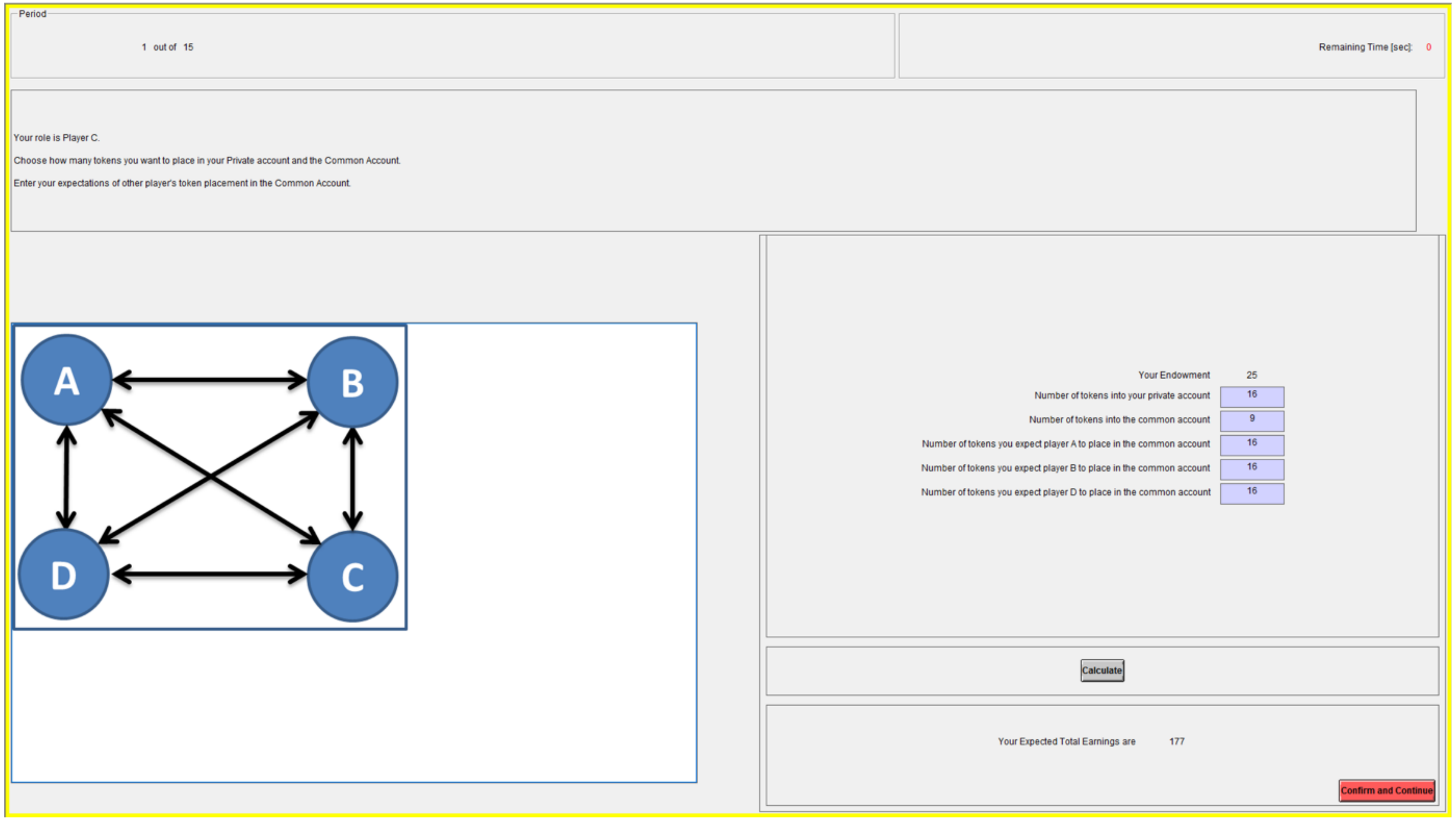


Figure I.2: Page 2: Feedback on subject's earnings from private account, common account and stage 1

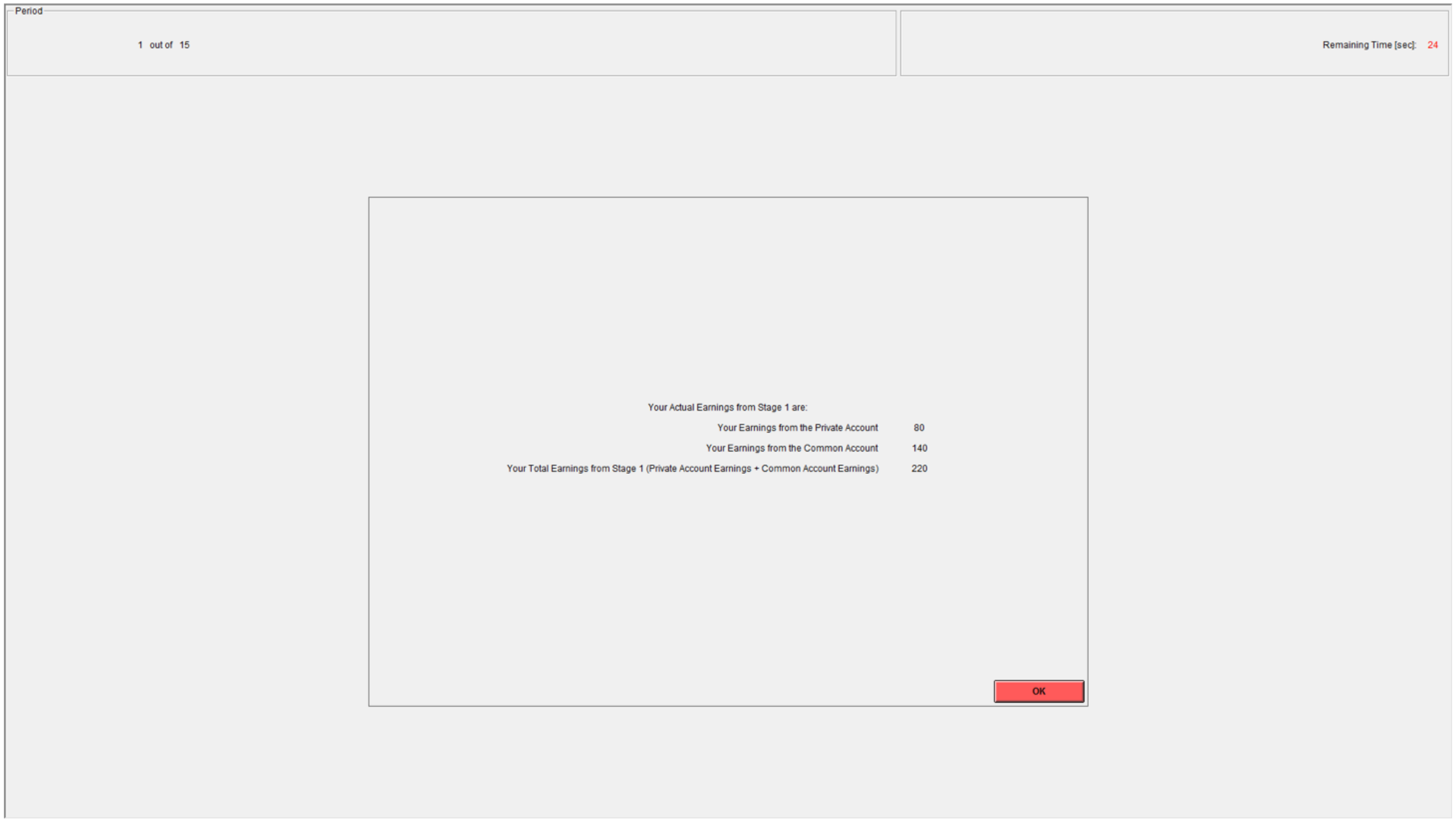


Figure I.3: Page 3: Punishment decisions

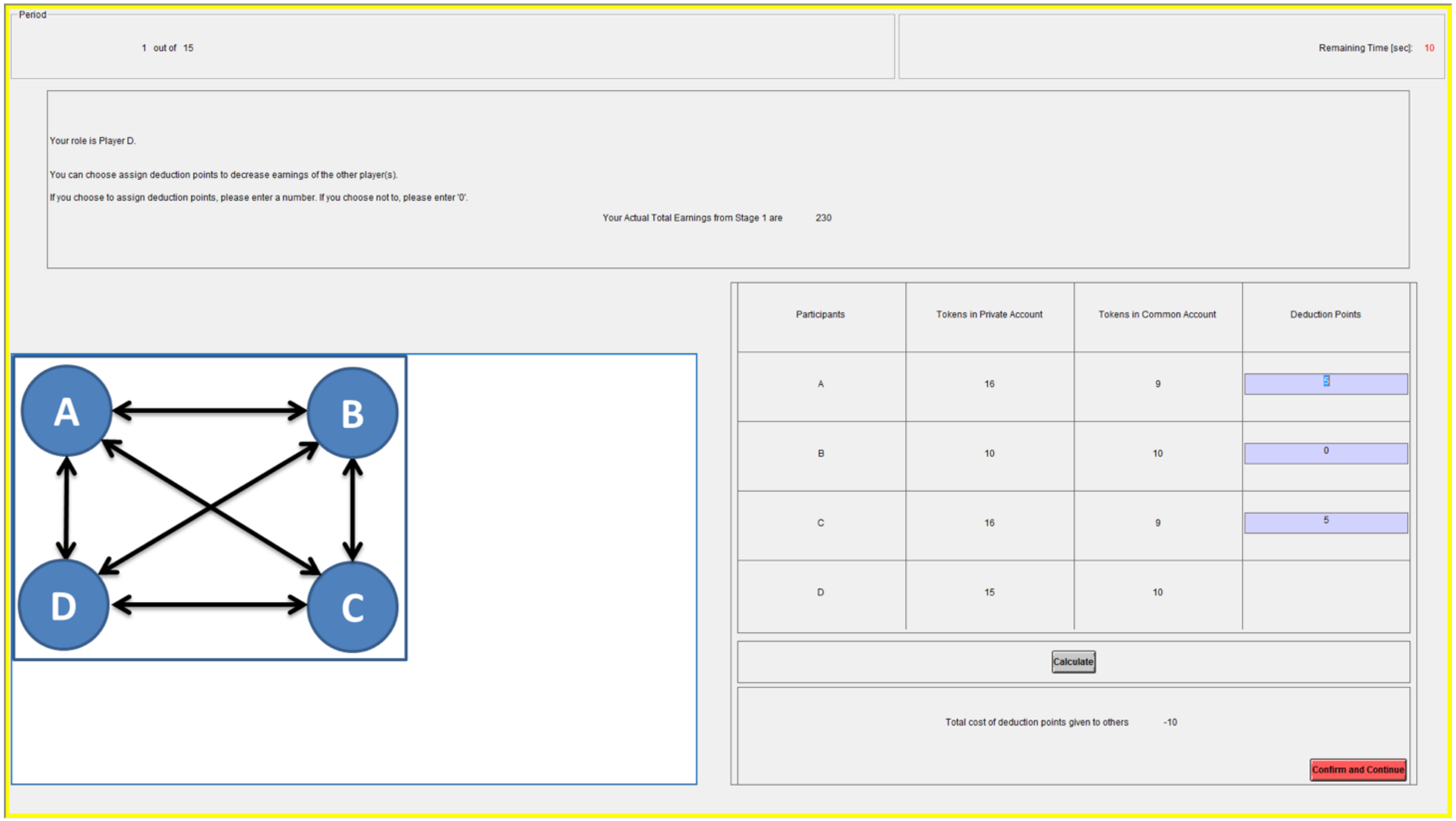


Figure I.4: Page 4: Feedback on cost of deduction points and subject's payoffs after stage 2