Essays in Behavioural Public Policy

Chiara Sotis

Department of Geography and Environment

London School of Economics

A thesis submitted to the Department of Geography and Environment
of the London School of Economics for the Degree of Doctor of Philosophy in Environmental Economics

London, 30 March 2023

About this PhD

I started this PhD in 2018 as a self-funded student with the aim of investigating what makes behavioural interventions in the environmental domain successful. Throughout the PhD I taught during term time and in the summer schools. I did this because I wanted to have the opportunity to work on research with an impact and I knew that LSE was the right place to make this happen. In my first year I studied the literature and worked on an idea for a randomised controlled experiment. I developed the design of the RCT, presented the idea in our internal seminars and contacted a charity to work with. However, when the pandemic hit it was clear that the project was not going to be feasible. After this, I looked for every opportunity I could find to test my ideas for behavioural interventions experimentally. The result of that search was a long-standing collaboration with junior Law researchers. This collaboration, which led to many of the papers included in this thesis, greatly benefited from our different backgrounds and expertise. Working with scholars from a different background allowed me to take the lead on the economics of the papers, the design of the experiment and the presentation of the data, while giving me valuable insights on how to best convey the policy implications of our findings. When we first started working together, I wanted to work on projects that would be relevant for policymakers in the environmental domain. However, the arrival of the pandemic changed priorities for policymakers (and funding) and my co-authors and I made a conscious attempt to work on research that would be helpful to society in a different way. Whether I succeeded in this respect is for others to judge, but getting to the end even with the odds stacked against me feels like a step in the right direction.

Declaration

I certify that the thesis I have presented for examination for the MPhil/PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it). The copyright of this thesis rests with the author. Quotation from it is permitted, provided that full acknowledgement is made. This thesis may not be reproduced without my prior written consent. 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 approximately 39900 words, excluding all appendices and the bibliography.

Statement of Conjoint Work and Inclusion of Previous Work

In this thesis I present 6 chapters, 5 of which are co-authored:

Chapter 1 Odi et Amo: A nudge to reduce the consumption of single-use carrier bags. This paper is co-authored with Alessandro Romano. This work is published on Waste Management with the same title. We both worked on the idea and wrote the paper. I was responsible for the methodology and all the analysis. I contributed 50% on this paper.
Chapter 2 Climate visuals: The effect of colours on understanding, concerns and policy preferences. This paper is jointly written with Vittoria Battocletti and Alessandro Romano. All authors worked on the idea and wrote the paper. I was responsible for the methodology and all the analysis. I contributed 50% on this paper.
Chapter 3 The scale of Covid-19 graphs affects understanding, attitudes, and policy preferences. This paper was jointly written with Alessandro Romano, Goran Dominioni and Sebastián Guidi. This work is published on Health Economics with the same title. All authors worked on the idea and wrote the paper. I was responsible for the methodology and all the analysis. I contributed 45% on this paper.
Chapter 4 Covid-19 Vaccine Passport and International Travelling: The Combined Effect of Two Nudges on Americans' Support for the Pass. This paper

was jointly written with Miriam Allena, Renny Reyes and Alessandro Romano. I am first author on this paper. Given my role as first author and my substantial contribution to the paper, I deem the paper to be largely the result of my work. This work is published on the International Journal of Environmental Research and Public Health with the same title. The idea for this paper is mine. All authors wrote the paper. I was also responsible for the methodology and all the analysis. I contributed 90% on this paper.

Chapter 5 Interactions between concerns for the environment and other sources of concern in 31 European countries. This paper is jointly written with Addolorata Marasco and Alessandro Romano. This work is published on Environmental Research Letters with the same title. Alessandro and I worked on idea. All authors wrote the paper. I was responsible for the statistical analysis while Addolorata was responsible for the mathematical analysis. I contributed 33% on this paper.

In all the co-authored work I have been the lead on all economic thinking, modelling and analysis as well as on presentations of the papers in conferences. Chapters 1-4 are co-authored with law scholars, while Chapter 5 is co-authored with a law scholar and a mathematician. Chapter 6 is single-authored.

Acknowledgements

This thesis is the end of a long journey, and hopefully the beginning of a longer one. This PhD wouldn't have been possible without the many people who helped to keep me sane and pushed me to keep going. I'll be forever thankful for their presence in my life, be it brief or consistent.

I was lucky to meet many women who inspired me throughout the PhD and I want to thank them before anyone else for all they did for me.

I am indebted to Susana Mourato, who gave me the opportunity to start this long journey and continues to be an inspiration for where this might lead. Your kindness and trust in me meant and mean a lot.

Thank you to Dimitra Petropoulou, who has been more than a mentor and a friend. Thank you for all your advice, for the food and stories we shared, for inspiring my teaching and guiding me through the years. I wouldn't be who I am now without you.

Thank you to Judith Shapiro, a pillar of strength in times of need and a reliable friend at any hour of the day. You allowed me to grow at my pace, but questioned me and pushed me to do and be better than I was. Thank you for your trust and for sharing so much of you with me.

Thank you to Margaret Bray, who believed in me before many others. Our teas and your way of teaching (micro)economics will stay with me forever. Thank you for being there for me and allowing me to hope that one day I would start and finish this journey.

While I'll never be able to list everyone who helped along the way, I want to acknowledge and thank some of the people who made this possible and infinitely better than it could have been.

My infinite gratitude goes to Tim Besley, for believing in me and allowing me to contribute so much to a core course at LSE, but also for showing me that more technical work doesn't need to be detached from reality. You serve as my role model for what an economist should be, do and know and I can never repay you for your trust and advice.

I thank (Ales)Sandro Romano, without whom I wouldn't have started the PhD, let alone finished it. Without you I don't think I would have ended up in academia. For all our papers (and fights related to them!), talks and for being a wonderful co-author and friend, thank you.

Thank you to my co-authors and especially to Vittoria Battocletti, Goran Dominioni and Sebastián Guidi, our long conversations made my research and my life better. I also want to thank Giles Atkinson, Stavros Georgiou and Davide Contu, for allowing me to work on a great project and always allowing me to have my say. Thank you to Ian Ayres, as a co-author and an inspiration. I never met anyone capable to do good research in so many fields. I'm still in awe I ever got to interact with you.

I owe most of what I know about behavioural economics to Matt Levy (but don't fault him for everything I still need to learn!). Your courses put the economics back into behavioural for me and your reading lists have been the basis of my research. Thank you for making me (re)appreciate micro theory and not sending me away whenever I had doubts or questions.

Thank you to Francesco Nava, for your encouragement throughout the years and for giving me precious perspective in times of need. Meeting you in the corridor always makes the day a bit better.

Thank you to Ben Groom and Frank Venmans, who have both seen only half of this path as my supervisors, but encouraged me to push myself until the end.

I thank the faculty and students in the Geography department who provided great feedback in my presentations, and in particular Antonio Avila, Pedro Llanos-Paredes, Julien Picard, Lorenzo Sileci, Yang Zheng and Pia Andres, who heard me complain about life one too many times but were still willing to listen. Lorenzo, your support and ability to spur me in the last mile of this has been really precious.

Thank you to all the economists and current or future doctors that gave me hope that I too would finish this adventure and allowed me to vent whenever I needed to in the many years we shared in 32L: Kasia Krajniewska, Evgeniya Kudinova, Niclas Moneke and Giuseppe Rossitti. Our coffees and conversations made my days better and gave me vital perspective on life.

Grazie agli amici che mi sono rimasti accanto nonostante lo stress e la distanza: Ambra, Filippo, Giuseppe (yes, you get a double mention for all you did!), you hold a special place in my heart. Thank you to Gary, who saw all the struggles that working and doing a PhD at the same time created. I'm thankful for your presence on the good and bad days.

Thank you to the people I haven't known for long but made a big difference for my quality of life in the last year: the Econ volleyball group, Andrea Herrera, Emiliano Rinaldi and Romano Tarsia.

Thank you to all the faculty members who allowed me to teach on their courses and to the students who, for reasons I don't fully understand, listened to me for hours and nominated me for awards. If I managed to help any of you along the way this was worth it.

A special thank you to Pete Mills, the best PhD Coordinator. You motivated me when I really needed it and made our wonderful conference happen!

Thank you to the people two steps away from my office who made me smile on bad days and encouraged me on good ones: Deborah, Sarah, John, Narmin, Kelly, Alice, Sharon, Lorna, Mini, Emma and Dária. Your friendly faces and advice made this experience much better.

A big thank you to my parents, my grandma Anna and my uncle Fabio. You have been the recipient of much good and bad news, I'm sorry for stressing you out, but very thankful you were there to support me. You watched me fall and get back up, ready to help when needed but allowing me to grow on my own at each step of the way and that means a lot to me. Thank you to Giulia, who didn't get to see the end of this journey. Your memory stays with me and I hope looking down you might reiterate that I'm a tad over-dramatic but smile anyway.

Thank you to Dropckick Murphys and Rancid. Since the beginning of the PhD I've been on stage with Dropkick Murphys three times, so it seems only fair to include them here- my teenage self would never forgive otherwise. The hours listening to your music made the world around that much easier to handle.

Last but really not least, thank you to the sea and the wind, longtime companions of my larger journey in life and my reason to always try to do a bit more and be a bit better. You make me feel at home no matter where I am.

I'm sure that despite taking the time to think about this list I have forgotten others who have been instrumental to me getting to where I am today. I've never been too good at being tidy and precise, and have always been bad at goodbyes so forgive me for not including you.

Finally, an ex post but important addition to the list: I wish to thank my examiners, Liam Delaney and Alessandro Tavoni. The viva was a beautiful experience and your comments were very helpful in thinking about the next steps!

Abstract

This thesis explores the impact of novel interventions in the environmental and health domains, and specifically investigates conditions to increase their effectiveness. In my first chapter I present evidence from a field experiment leveraging place attachment and football preferences to reduce the use of carrier bags in supermarkets. I find that the treatment reduces the use by 8-12% and that the effect persists even after the end of the treatment period. I propose ways in which a regulator can scale up this intervention at virtually no cost. In my second chapter I present the results of two online experiments studying whether the choice of colours in the visuals included in the IPCC Report affects the support for policies aimed at mitigating global warming. The results show that some colour schemes can affect understanding of climate visuals and participants' support for a carbon tax. In the next two chapters I study the role of framing in shaping support for policy responses to the Covid-19 pandemic. In chapter 3, I show that when the number of Covid-19 related deaths is reported on a logarithmic scale people have a less accurate understanding of how the pandemic has developed, make less accurate predictions on its evolution, and have different policy preferences than those who are exposed to the same data on a linear scale. In my fourth chapter I study preferences for Covid-19 immunity passports for international travel and whether two nudges, used in isolation or together, foster support for their adoption. I find that both nudges increase the support for the passport and that their impact is stronger when they are used together. In my experiments I find that the level of worry about an issue influences behaviours and policy preferences, so I devote my fifth chapter to study how different concerns interact in people's minds. I show that theories that were previously perceived to be mutually exclusive can coexist. I find that the relationship between the concern for the environment and the economy is often asymmetric: concerns for the economy typically reduce concerns for the environment, while concerns for the environment foster concerns about the economy. In the final chapter I present a theory model that builds on the findings of the previous papers. I introduce a two-period model of reference-dependent preferences where (behavioural) interventions are a signal agents receive between the periods. The signal causes a biased Bayesian updating that leads to different choices in the second period. I show that this can explain heterogeneity in treatment effects and hence that a single model of preferences can explain polarisation and convergence of opinions.

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Preface: A brief history of the research that led me to pursue a PhD

In the beginning, Adam Smith created economics. To those interested enough in sacred books listing the main character first seems like the right way to begin any writing, so why not this thesis? I first encountered his work in high school, where a butchered version of his thoughts and those of many other economists became the subject of unbearable lecture hours in which I thought I would do anything but study economics. I was considerably luckier in university, when Luca Fiorito, leading my history of economic thought course, introduced me to the Theory of Moral Sentiment, a far better piece of work than Smith's most famous and one that deserves more attention that what it typically receives. If you were to ask behavioural economists who created the field, many may claim it was (involuntarily) Gary Becker, who first used the notation in the 1970s to describe rational choice theory. A little ironic given what we take behavioural economics to mean these days. I prefer those who credit Smith for it- after all, the Theory of Moral Sentiment starts by introducing externalities and reasons for pro-social behaviours

> "How selfish soever man may be supposed, **there are evidently some principles in his nature, which interest him in the fortune of others, and render their happiness necessary to him**, though he derives nothing from it except the pleasure of seeing it. [...] **that we often derive sorrow from the sorrow of others, is a matter of fact too obvious to require any instances to prove it**; for this sentiments, like all the other original passions of human nature, is by no means confined to the virtuous and humane, though they perhaps may feel it with the most exquisite sensibility."

I wonder how much happier my days in high school would have been if instead of Adam Smith the invisible-hand creator I had been introduced to Adam Smith, the behavioural economist. As the field began to grow a large portion of the (beautiful) seminal papers in behavioural economics attempted to uncover predictable ways in which humans deviate from neoclassical theories. The authors started by showing compelling evidence of deviations, created a model that could explain them and proposed ways in which the bias could be reduced or eliminated. But behavioural interventions were not quick to become mainstream. It took the publication of Thaler and Sunstein's Nudge: Improving Decisions About Health, Wealth and Happiness to generated an unprecedented whirlwind of interest in them. Suddenly, behavioural interventions became the object of interest of academics, public and private sector workers. Researchers from different fields started testing different treatments, and policymakers became intrigued by the seemingly high-effect low-cost policies proposed by the literature. In 2009, the US government recruited Cass Sunstein as head to The Office of Information and Regulatory Affairs (OIRA) to streamline regulations. In 2010, the UK established the first Behavioural Insights Unit (BIT) on a trial basis, under the Cabinet Office. Shortly after, other countries followed suit and the OECD now lists over a hundred behavioural units as part of local or national government and across the private and public sectors. For over a decade now, it has been clear that behavioural social scientists have something to contribute to the policy-making discourse. But years of testing different treatments and scaling up existing ones led scholars to question whether these interventions were really working as well as the original papers suggested they would. Are people really saving more than before? Did it get any easier for people to keep up with their gym classes? Do colour-coded labels improve food choices? Can nudges really help in the fight against climate change? Recent evidence suggests that scaling up behavioural interventions is not easy to say the least. Sometimes they scale up well, but other times the large effects found in controlled experiment seems to vanish, or at least induce more subtle changes than initially hoped. But this didn't lead to shutting down the hundreds of behavioural units. Well-designed interventions are too appealing to give up on and they are here to stay and (hopefully) help. Our focus then should be to try and understand what is it that makes some treatments succeed and others fail- we need a more thorough understanding of *why and when* treatments are effective. We need more testing of novel mechanisms, to see if anything can work better than those we identified. But we also need to see if the ones we have seen working stand the test of time and external validity. I see the collection of papers in this thesis as a step in this direction.

Introduction

In this thesis I explore what makes behavioural interventions in the environmental and health domains effective. In my first chapter I study how to reduce the consumption of single-use carrier bags in supermarkets. Single-use carrier bags pose a large threat for the environment, but their consumption is still widespread, with over 5 trillion bags used each year. Repeated attempts to curb their consumption, including the imposition of a levy on their purchase, showed limited success. I present evidence from a field experiment leveraging place attachment and football preferences to create a system of carrots and sticks and reduce the use of single-use carrier bags. The system consists of a donation to an an "anti-charity" (an institution that is likely to be perceived negatively by the buyer) for each bag bought and a donation to a local charity for each shopper not needing a bag. I show that this intervention reduces the daily consumption of bags by 8-12%, persists even when the donations stop, and can easily be used by regulators at virtually no cost by creating multi-city tournaments.

In my second chapter I present evidence on the impact of the colours used in climate visuals on the support for policies aimed at mitigating global warming. Colours are a crucial component of visuals and the IPCC recognises their importance and produces extensive guidelines on how to structure their figures. However, there is limited evidence on the impact of using specific colour combinations to convey complex information. This paper tests whether schemes with higher semantic discriminability influence understanding and policy preferences. My data shows that some colour schemes can affect Republicans' understanding of climate visuals and their stated support for a carbon tax, but ignoring standard symbolism does not lower the average level of comprehension.

In my third and fourth chapter I study how framing influences the support for policy responses to the recent pandemic. Since its arrival, Covid-19 disrupted lives and economies. People were routinely exposed to a vast amount of information meant to allow them to form policy preferences, but how much could they process? Especially before the arrival of the vaccine, people's understanding of the evolution of the pandemic was a crucial driver of their support for policies to mitigate the spread of the virus. In my third chapter I show that the choice of the scale adopted to report Covid-19 data has important consequences on how people understand and reacted to the information conveyed. I show that when the number of Covid-19 related deaths is reported on a logarithmic scale, people have a less accurate understanding of how the pandemic has developed, make less accurate predictions on its evolution, and have different policy preferences than when they are exposed to the same data on a linear scale.

In my fourth chapter I study preferences for Covid-19 immunity passports for international travel and whether two nudges, used in isolation or together, can help fostering support for the passports' introduction. I contribute to the literature in two main ways. First, I add to the theoretic literature testing the interaction of nudges. I show that a nudge relying on the status quo and one relying on peer pressure are complementary. Second, I study people's support for a Covid passport at a time when this was deemed crucial to reopen international travel. I show that both nudges increase the support for the Covid-19 passport and that their impact is stronger when they are used together.

In my initial chapters I show that the level of concern people have over an issue shapes their policy preferences. But worries do not form in a vacuum and how worried people are about an issue is likely to depend on how worried they are about other issues. One of the main theories on how worries interact in people's minds is the finite-pool-of-worry hypothesis. This states that humans have limited resources to worry, thus worrying more about one issue lowers their concern about others. Conversely, the affect generalisation theory posits that an increased level of worry about one threat increases concerns about related issues. In my fifth chapter I use a Lotka-Volterra model and Eurobarometer data from 31 countries to study how different worries interact in people's minds. I am the first to show that both leading theories can co-exist. I find that on average higher concerns for the economy lower the level of concern for the environment. Instead, increases in concerns for the environment favour the growth of concerns for the economy.

Finally, in my last chapter, I present a theory model to rationalise the findings of the papers included in the thesis. I introduce a model of reference-dependent preferences that accounts for utility agents derive from stated preferences and material consumption. I introduce (behavioural) interventions as a signal agents receive between the two periods which causes updating in a biased fashion. I show that this can explain heterogeneity in treatment effects and hence that a single model of preferences can explain polarisation and convergence of opinions.

Overall, this thesis shows evidence of effective behavioural interventions that can help in the fight against climate change and during times of crises like a global pandemic. My results warn policymakers about the dangers of promoting multiple sets of policies at once and set the agenda for pinpointing the mechanisms that make these interventions effective.

Chapter 1

Odi et Amo: A Nudge to Reduce the Consumption of Single-Use Carrier Bags

1.1 Introduction

Plastic bags and biodegradable bags are extremely dangerous for the environment (United Nations, 2018; European Commission, 2018; Napper and Thompson, 2019), but they are consumed in large quantities. Recent data from the United Nations reveals that 5 trillion plastic bags are used each year (United Nations, 2018). Italians are also heavy users of plastic bags: 95% of them uses one or more plastic bag per week (Codacons, 2019), and only 28% reports using those bags more than once. The majority states that they just throw the bags away after one single use (Codacons, 2019).

Italian regulators have repeatedly attempted to reduce plastic bags consumption, but with limited success. For instance, building on the European Directive 2015/720/UE, the Italian government has banned traditional plastic bags, so that now Italian stores are allowed to sell only biodegradable ones. But store owners and the general population have not reacted as expected. A recent investigation conducted by Altroconsumo in 11 Italian cities - including Milan, Turin and Rome - revealed that about half of the plastic bags sold in supermarkets and smaller stores are not biodegradable, and hence are illegal (Altroconsumo, 2018). Another recent survey shows that only slightly more than half of Italian consumers are aware that traditional plastic bags are banned, thus shop owners can sell illegal bags with little risk of being reported (Codacons, 2019). These facts suggest that traditional top-down approaches are not always effective to address the problem posed by plastic bags, or even to make people aware that there is a problem.

In any case, switching to biodegradable bags would be no panacea for at least three reasons. First, their production process releases harmful chemicals in the atmosphere, and requires the use of large quantities of fertilizers and pesticides (Tabone et al., 2010; Phys.org, 2017). Second, biodegradable and oxo-biodegradable bags that are not properly treated have very low deterioration rates, especially in soil and marine environments (Eerkes-Medrano et al., 2015; Napper and Thompson, 2019). Therefore, they can still pose a serious threat for biodiversity, maritime industries and human well-being. Third, current standards to assess whether plastic is biodegradable are insufficiently accurate in predicting the biodegradability of carrier bags in different environments and do not include toxicity testing in aquatic environments (Harrison et al., 2018). Unsurprisingly, the European Union called for additional measures to reduce consumption of biodegradable bags (European Commission, 2018).

In response to this call, in this article we test in a real-world context an innovative form of nudging to induce people to minimise the consumption of single-use bags. The main goal is inducing people to bring their own reusable bag from home. We base the nudge on the literature on sticks and carrots as drivers of actions. One problem to solve when devising an effective nudge in this context is that the demographic characteristics of supermarket customers are very heterogeneous, and hence it is very hard to devise tailored interventions. What might be effective for one category of customers might be counterproductive for another. However, we argue that grocery is a highly geographically localised activity, since people generally shop in close proximity to their homes. This creates a unique opportunity to devise systems of carrots and sticks that exploit preferences that are homogeneous at the geographical level. Sport preferences present this feature. In fact, sport teams are generally strongly connected with a well-defined geographic location in which most of their supporters tend to concentrate. Moreover, people located in a certain area generally share a distaste for the same rival teams.

Therefore, the proposed nudge exploits football preferences to induce people to bring their own reusable bag from home. It consists in placing two buckets next to each cashier in a supermarket in Naples, Italy. On one of the buckets there is the logo of Juventus, the football team that is despised by most Neapolitans (i.e., the "anti-charity"). On the other bucket there is the logo of an association that helps local children and that is likely to be perceived positively by the customers of the supermarket (i.e., the "charity"). When a customer purchases a bag in the supermarket the cashier adds 0.1€ in the anti-charity bucket. Instead, when a customer does not purchase a bag the cashier moves 0.1€ from the anti-charity bucket to the one of the charity. At the end of each week we donate the money in the buckets to the charity and the anti-charity. This treatment significantly reduced the consumption of single-use carrier bags per person, even if it did not impose any additional cost on the customers of the supermarket. Additionally, we observe that the number of reusable bags purchased did not increase during the treated period. This suggests that supermarket customers were bringing their own bag from home more frequently. We conclude by showing that the proposed nudge can be used by regulators at virtually no cost (i.e., without requiring monetary donations) and explain how this could be done.

1.2 Related literature

This work relates to several strands of literature. To begin with the experiment builds on the works on nudging. Nudging has proven to be an effective means to modify individuals' behaviours by changing the choice architecture that surrounds their decision (Thaler and Sunstein, 2008). Nudges have already been used to foster pro-environmental behaviours like reducing water (Ferraro and Price, 2013) and electricity consumption (Allcott, 2011). Moreover, Nudging has been used to reduce carrier bags consumption. In an online experiment, Chandra (2023) showed that changing the framing of the question regarding carrier bags at the checkout can affect customers' consumption of single use bags. In a different context, Rivers et al. (2017) show the impact on the consumption of reusable bags of a disposable bag levy of $0.05 per bag introduced by the City of Toronto (which they consider a nudge). They find that after the introduction of the levy the number of people that brought a reusable bag increased by 3.4%. They argue that this is evidence that people consumed less plastic bags while the levy was in place. Other studies found much larger effects. For instance, Martinho et al. (2017) found that in Portugal a tax of €0.1 per plastic bag caused a reduction in plastic bags consumption of 74%, and an increase in the demand for reusable bags of 61%. Similar results were reported in Washington, DC after the introduction of a levy of $0.05 for both plastic and paper bags (Washington Department of Energy and Environment, 2016). However, Rivers et al. (2017) correctly note that these studies are likely to overstate the impact of the levy because they estimate the effect by a simple difference in means. Since the consumption of plastic bags is decreasing due to the evolution of social norms, this approach is not suitable to isolate the impact of the fee (Clapp and Swanston, 2009). Rivers et al. (2017) substantiate this claim by showing that using a simple difference in means approach overstates by almost ten times the impact of the levy imposed by the City of Toronto. However, it is worth emphasising that Rivers et al. (2017) analysed self-reported use of reusable carrier bags, instead of gathering data on the actual consumption of reusable and disposable bags.

So far, net of outright bans, most of the initiatives attempting to reduce the consumption of carrier bags have been based on monetary incentives (Xanthos and Walker, 2017; Nielsen et al., 2019). In fact, the only reason why Rivers et al. (2017) consider a nudge the levy imposed in Toronto is that its value is very small. However, in this context using money is problematic for at least three reasons. First, the small sum that is charged for plastic bags is unlikely to induce many people to bring a plastic bag from home. People do not go to the supermarket on a daily basis,[1] and hence an effective treatment must stick in the mind of the consumers for days. Charging $0.05 per bag is unlikely to achieve this result. Unsurprisingly, studies highlighted that even consumers willing to reduce their consumption of plastic bags regularly forgot to bring their own bags (Musa et al., 2013; Zen et al., 2013; Bartolotta and Hardy, 2018). Second, customers might perceive the levy as a "price" they pay to be allowed to pollute the environment. There is robust evidence that when a payment is perceived in these terms it might even backfire and increase the undesirable behaviour (Gneezy and Rustichini, 2000). Third, empirical evidence suggests that even taxes and levies that successfully reduce single-use carrier bags when they are implemented become less effective over time (Jiang, 2016).

For these reasons, we suggest that policymakers should expand their portfolio of tools and explore the possibility of using non-monetary nudges. This is even truer in the case of Italy due to the reported tendency to circumvent plastic bags bans (Altroconsumo, 2018). Therefore, this work contributes to this literature by showing that non-monetary nudges can be used to reduce consumption of single-use carrier bags.

The experiment relies on findings from the literature on in-group cooperation and out-group hate, e.g., Weisel and Böhm (2015). This literature finds that individuals are willing to engage in behaviours that are costly when they perceive that their group is under threat (Weisel and Böhm, 2015). An important insight from this literature is that inter-group conflict is different from conflict at the individual level. At the individual level, there is a preference for maximising social welfare, hence individuals are willing to bear a little personal cost if this contributes to overall social welfare (Charness and Rabin, 2002; Choshen-Hillel and Yaniv, 2011). On the contrary, in the case of group-level conflicts, individuals are more willing to incur a cost when they can inflict a harm on the out-group (Weisel and Böhm, 2015).

We incorporate this insight in our treatment by relying on the works on anti-charities (Ayres, 2010). The basic idea behind these works is simple, yet powerful. It is well-known that commitments can be effective in promoting a certain behaviour (Thaler and Sunstein,

[1] For instance, data on United States reveals that people go for grocery 1.5 to 2.2 times per week (Statista, 2018)

2008). An individual is more likely to perform a given task (e.g., eat healthy), if she faces a sanction in case she does not perform the task (e.g., she eats fries). These works suggest that the commitment device is even more effective if the sanction benefits an anti-charity. Consequently, we structure our treatment so that when customers buy a bag €0.1 is donated to the anti-charity. Vice versa, the customers that engage in the pro-environmental behaviour benefit a charity and harm an anti-charity, since the cashier will move €0.1 from the bucket of the anti-charity to that of the charity.

1.3 Experimental Design

1.3.1 The Choice of the Anti-Charity and the Charity

Using sport teams as anti-charities presents three advantages. First, football preferences tend to be geographically homogeneous, so that often supporters of a given team are clustered in a certain geographical area. Similarly, most people in a given area share a "common enemy" as also football rivalries tend to follow geographical boundaries. Consider, for instance, the strong rivalry between Real Madrid and Barcelona, with the supporters of the former largely concentrated in Madrid, while the supporters of the latter concentrate in Barcelona. Similar patterns also characterise sports other than football. New York Yankees fans are often based in New York, whereas the Boston Red Sox fans concentrate in the Boston area. Therefore, since grocery is a geographically localised activity, most of the people shopping in a given supermarket are likely to have fairly homogeneous sport preferences.

Second, football preferences and rivalries are taken very seriously by football fans, and therefore lead to the spontaneous emergence of groups and "tribes" (Giulianotti, 2011; Newson, 2017). Additionally, football is widely followed by both men and women. According to a recent survey, 81% of the Italian "active" population (i.e., between 18 and 65) affirms to be interested in football (Repubblica, 2017), and the same percentage of women watches at least some football matches (TGCom24, 2014). These data reveal that virtually everybody is exposed to some information related with football, at least indirectly. Consequently, a treatment involving a football team could facilitate an individual's identification with a group, and hence her willingness to engage in behaviours that would increase the group's welfare (Brieger, 2019). In fact, there is evidence that people are more willing to cooperate when they identify strongly with a social group (Buchan et al., 2011).

Third, football preferences are likely to be salient for young males, a segment of the population that is increasingly purchasing in supermarkets (Wagner, 2017), but that perceives reusable bags as feminine and therefore consumes a disproportionately large number of bags (Brough et al., 2016). In particular, this treatment might ensure that bringing one own's bag would no longer perceived as "uncool" or socially unacceptable among young males, which in turn could encourage them to engage in pro-social behaviour (Hannstein and Echegaray, 2018). More generally, our treatment could generate peer pressure against purchasing plastic bags in the supermarket to avoid donating to an association connected to Juventus. Since peer pressure is a strong determinant of people's behaviours (Cardinale Lagomarsino et al., 2017), this could result in lower numbers of single-use carrier bags being consumed.

Napoli is the ideal location to test whether football teams constitute effective anti-charities. In fact, unlike other Italian cities, Napoli has only one football team that is supported by almost every Neapolitan. As importantly, all Napoli fans consider Juventus their "sworn enemy". Recent data suggests that 97% of Napoli supporters consider Juventus as the team they dislike the most (Demos-Osservatorio Capitale Sociale, 2016).

Instead, to identify the charity we build on the literature on place attachment (Altman and Low, 2012), and select an association that helps local children. The basic idea behind this literature is that individuals can create meaningful bonds with places, and that these bonds have a significant impact on their behaviour (Scannell and Gifford, 2010). Additionally, it has been shown that place attachment can be used to foster environmentally responsible behaviour (Vaske and Kobrin, 2001). For this reason, we pick a charity that is strongly connected with the place in which we implement the treatment. This should also help us to influence the behaviour of customers that are not interested in football.

1.3.2 The Treatment

In this experiment, we treated a supermarket in Capodimonte, an area of Napoli that is renowned for a Museum that exposes paintings of artists like Caravaggio, and for the forest in which the museum is located. The supermarket we treat is just outside of the touristic area, and hence its customers are almost exclusively people living in the neighbourhood. Currently, its customers can buy a small biodegradable bag for €0.05 or a large biodegradable bag for €0.1. Alternatively, they can purchase reusable bags for either €0.5 or €1. We do not distinguish between the small and large biodegradable bags in the treatment. The two types of bags differ only in size, with the small ones measuring 27x50cm and the large ones 30x60cm, hence they are unlikely to have substantially different production processes or environmental impacts. This has the added benefit of simplifying our treatment.

The treatment that we implement lasts for four weeks, from 17 June 2019 to 14 July 2019. We note that Napoli played the last official match of the 2018/2019 season on the 25th of May, hence no official matches were played during the treatment. The treatment consists in placing two buckets next to each cashier, each one filled with euro €10 worth of €0.1 coins. On one of these buckets there is the logo of the charity "A' Voce d"e Creature", an ONLUS that is committed to helping Neapolitan Children.[2] On the other bucket we placed the logo of an anti-charity: Juventus, the rival football team. When a customer purchases a biodegradable bag in the supermarket the cashier adds €0.1 in the Juventus bucket. Instead, when a customer does not purchase a bag the cashier moves €0.1 from the Juventus bucket to that of the charity. We placed a poster in the supermarket that explained the mechanism of donations (see Figure 1.1). To isolate the effect of the mechanism of donations, in the poster we did not provide specific information on why bags harm the environment. Indeed, while the poster showed a cartoon with bags and asked to keep Naples clean, there was no appeal to environmental attitudes, nor any plea to stop consuming bags because of the damages they impose on the environment.

At the end of each week, we donated the money in the charity bucket to A' Voce d"e Creature, and the money in the Juventus bucket to "Gli Insuperabili", an ONLUS connected to Giorgio Chiellini, Juventus captain. If we had wanted to ensure that our treatment was as strong as possible, we should have donated directly to Juventus. However, we decided to donate to a charity connected to Juventus to minimise the risk that the experiment would have created discomfort among the clientele of the supermarket. Therefore, we make our donation to a charity that is strictly linked to Juventus and to one of its most representative players. This way, all donations are ultimately made to children in need.

To avoid deception, we informed the cashiers and specified on all posters that the money in the anti-charity bucket went to Gli Insuperabili and not to Juventus, however we also explained that the two were connected. While we cannot be certain that all customers read and understood who received the money, on average this is likely to have weakened our treatment. This suggests that our results understate the potential impact of a treatment based on charities and anti-charities. As we argue later, a policymaker that wants to rely on our scheme will be able to donate directly to charities and anti-charities.

After making the donations, we placed two kinds of small stickers in the supermarket

[2] ONLUS is an acronym that translates in "non-profit organisation of social utility".

Figure 1.1: Big poster explaining the functioning of the treatment. The text at the top translates to "Let's clean up Naples! When you come to the supermarket bring your own bag from home: help the children and keep Naples clean!" The bottom left text translates to "In the incoming weeks for every bag bought at the supermarket €0.1 will be donated to a charity sponsored by Juve. Instead, if you bring your own bag we will donate the equivalent to a charity that supports Neapolitan children." The donkey (symbol of Napoli) is saying "Napoli says stop to bags and little bags". The green sign says "Enough bags" and the bottom left text translates to "Don't act like a Juventus supporter, defend the city". Defend the city is a slogan of Napoli supporters.

indicating how much we had donated during the preceding week to the two ONLUS. We also placed in the supermarket the receipt of the donation, to show that we were really donating the sums collected (Figure 1.2). The message on the posters was adapted each week to reflect the donations we made.

To test the impact of the treatment we compare bags consumption during the treated period and two control periods. The first control period (hereinafter, control-2019) goes from May 20th 2019 to June 9th 2019. The second control period (hereinafter, control-2018) goes from May 21st 2018 to June 10th 2018 and from June 25th 2018 to July 15th 2018. To ensure that we correctly isolate the impact of the treatment, we eliminate from the sample the last week pre-treatment (from June 9th 2019 to June 16th 2019) and the first week of the treatment (from June 17th 2019 to June 23th 2019). It is well established that event studies aiming to measure the impact of new information must account for the fact that information leakages might confound the results.[3] Consider for example the case in which

[3] For instance, Bhattacharya et al. (2010) show that public announcements about a company do not affect its

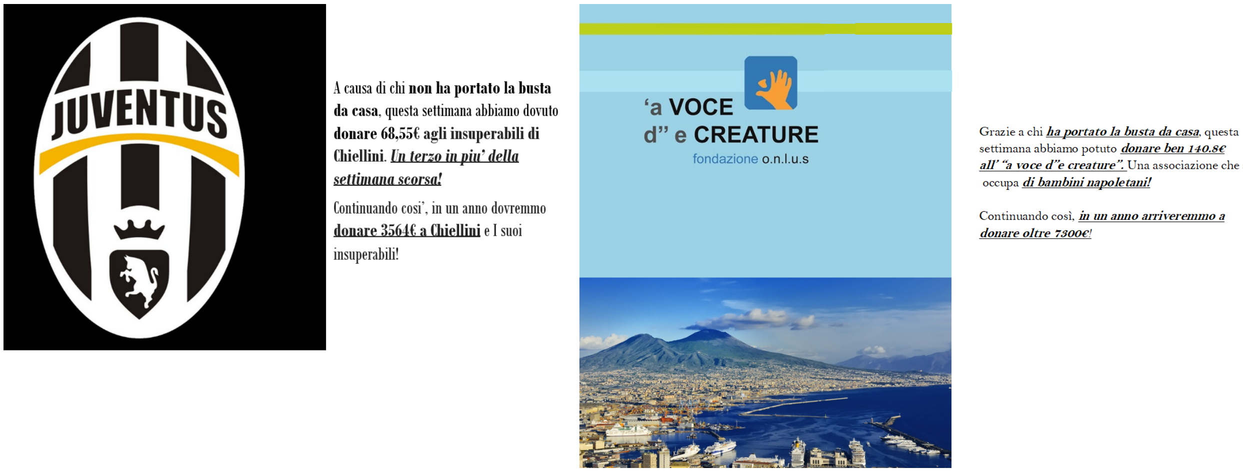

Figure 1.2: Example of a small Poster on the charity (on the left). The text translates to "Thanks to who brought his own bag from home, we could donate €144.6 to A' Voce d"e Creature, an association that helps Neapolitan children. If we continued like this for one year, we could donate €7519 to Neapolitan children!". On the right is an example of a small poster on the anti-charity. The text translate to "Due to the people that did not bring their own bag from home, this week we had to donate €52.15 to Chiellini's Insuperabili. If we continued like this for one year, we could have to donate €2700 to Chiellini and his Insuperabili"

the cashier discusses the experiment with the customers a few days before the treatment is implemented. Then, since the customers do not know exactly when the treatment will start, they are likely to start adjusting their behaviour as soon as they are informed by the cashier. In fact, before leaving the apartment - and hence when they have to decide whether to bring their bag or not - the customers cannot observe if the treatment has begun. This is similar to what would happen in a policy-setting: Since regulations are generally not kept secret until the day in which they are implemented, some of their effects might be observable before they enter into force. This is especially true when the regulated are not perfectly informed about the day in which the regulation will come into force.

Lastly, we exclude the first week because the full treatment starts only the second week. There are two key components of the treatment: (i) the large poster explaining the basic setup of the experiment; and (ii) the small posters in which we state how much we have donated/show the receipts of the donations. The second part of the treatment can only be implemented at the beginning of the second week.

To summarise, we consider the week prior the implementation of the treatment and the

share prices when its insiders are allowed to trade in the shares of the company. The reason is that traders react to the new information before it is made public, therefore the entire effect of the announcement is takes place before the announcement is made. In a similar way, when information about a treatment leaks, we expect that people start adjusting their behaviour.

first week after the treatment is implemented as transition period. Therefore, we exclude them from the analysis. Last, to ensure comparability and to carry out the difference-in-differences analysis, we eliminate the corresponding weeks from control-2018 (from June 11th 2018 to June 24th 2018).[4] For completeness, we also run all specifications considering the two transition weeks as part of the treatment. We find similar estimates for the effect of the treatment (the full tables are included in the Appendix).

1.3.3 Mimicking A Regulation

The goal of this paper is testing in a real-world context the impact on bags consumption of a possible policy based on charities and anti-charities. Therefore, in setting up the experiment we attempted to mimic what a regulator could and could not do when implementing a policy of this kind on a large scale (e.g., the entire city of Napoli). To begin with, we minimised the time we spent in the supermarket by entering the store only to put up the big poster and to update the information on the small posters. The reason is twofold. On the one hand, our presence in store could have altered the behaviour of the cashiers and the clients (experimenter bias). On the other hand, a regulator cannot ensure the constant presence of people supervising the treatment in each supermarket without incurring enormous costs. Second, we minimised the number of items that we placed in the store. In particular, at the beginning of the treatment we placed only *one* poster (297x420 mm) to explain and advertise the experiment. Moreover, at the end of each week we placed only several small stickers indicating how much we had donated to the charity and the anti-charity. This choice could seem counter intuitive, since placing many posters would have increased the visibility of the treatment and could have fostered awareness among the customers. However, before anything else, a supermarket is a business. Regulations that interfere excessively with the set-up of the supermarket are likely to be received negatively by the shop owner and could affect consumption choices. Third, we clarified to the cashiers that they would have no obligation to explain the treatment to the customers. This is because for a regulator it would be impossible to monitor and to enforce an obligation of this kind.

1.4 Statistical Analysis and Results

To test our hypotheses, we work with three different sets of data: the first dataset includes the treatment period, the control2019, the control-2018 and one week to test the persistence of the effect (July 16th, 2019 to July 22nd, 2019) (in the Appendix). The second dataset

[4] Since the number of clients and the revenues change on the various days, we ensure that the control-2018 period includes the same days (e.g., 3 Mondays, 3 Tuesdays, etc), as the treatment period.

includes the treatment period and the control-2019. The third dataset includes the treatment period, the control-2019 and the control-2018.

	All sample		2018		2019 pre-treatment		2019 treatment		2019 post-treatment	
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
bags	309.24	73.18	337.71	74.11	311.33	63.74	279.14	54.36	222.43	41.75
bagspp	0.59	0.09	0.63	0.09	0.60	0.09	0.54	0.05	0.46	0.08
clients	533.42	123.15	547.29	130.51	531.00	121.57	521.38	115.50	493.57	116.83
revenues	5714.73	1702.41	5739.34	1764.79	5863.56	1821.64	5673.89	1617.24	5243.02	1436.68
Observations	91		42		21		21		7	

Table 1.1: Means and standard deviations of the total amount of daily bags purchased (bags), the daily amount of bags per person (bagspp), the amount of clients per day (clients) and the amount of revenues per day (revenues) for the overall sample, the 2018 sample and the 2019 sample (pre-, during and post-treatment).

Table 1.1 presents the summary statistics for the variables considered: total number of bags used per day (bags), number of bags per person (bag per person), number of clients per day (clients), and revenues per day (revenues). We observe that from control2018 to control-2019 the total bags and the number of bags per person went down by approximately 7.81% and 4.8%, respectively. Moreover, in comparison to control-2019, during the treatment both total bags and bags per person decreased by around 10%. This data supports the idea that the consumption of bags is decreasing, but also that the treatment significantly intensified this trend. The data relative to the post-treatment week show a further reduction in the bags and the bags per person.

1.4.1 Difference in Means

First, we test whether our controls are valid. In particular, we check that the treatment did not induce some customers to shop elsewhere, and that customers did not change their shopping habits before or during the treatment. To do so, we check that there are no statistically significant differences in the number of clients and the daily revenues between the treatment period and the controls. Since we observe no such differences, we conclude that the control periods are valid and that the decrease in the number of single-use carrier bags is not attributable to a contraction in business volume.

We now turn to bags consumption. We start by looking at the difference in means between the bags sold during the treatment period and during the control-2019. As we observe a naturally decreasing trend in the number of bags consumed, we avoid any comparison between the treatment period and the control-2018. Results for both these tests can be found in Table 1.2.

	Differences in means for daily bags and bags per person purchased				
	Control(mean)	Treatment (mean)	Difference	Std. Error	Obs.
clients	531.0000	521.3810	-9.6190	36.5931	42
revenues	5863.5591	5673.8890	-189.6700	531.5673	42
bags	311.3333	279.1429	-32.1905*	18.2812	42
bags per person	0.5980	0.5437	-0.0543**	0.0226	42

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.2: Difference in means for daily clients, revenues, bags and bags per person between the treatment period and the 2019-control period.

The reduction in bags consumed is statistically significant for all the tests, suggesting that the treatment was effective. We find that during the treatment weeks the daily consumption of bags went down by 10.34% with respect to the control-2019. We observe similar results for the bags per person. We further show the impact of the treatment graphically in two boxplots, showing the distribution of total amount of bags and bags per person before and during the treatment (see Fig. 1.3). Last, we also find that there was no statistically significant difference in the number of reusable bags sold during the treatment period. This suggests that people did not start buying more reusable bags, but instead were bringing their own bag more often.

1.4.2 Regression Analysis

The data shows a decreasing trend in carrier bags consumption and some heterogeneity in the daily number of clients and revenues. To investigate the impact of the treatment on the total consumption of biodegradable bags and the biodegradable bags consumed per person, and to account for the heterogeneity in the daily number of clients and revenues, we run regressions controlling for the number of clients and the revenues.

We run six specifications: 1) total number of bags controlling for the number of clients, 2) total number of bags controlling for clients and revenues, 3) total number of bags controlling for clients, revenues and revenues per person, 4) bags per person controlling for clients 5) bags per person controlling for clients and revenues and 6) bags per person controlling for clients, revenues and revenues per person. The specifications we run are:

$$\hat{Bags}_t = \beta_0 + \beta_1 treatment_t + \beta_2 clients_t \tag{1.1}$$

$$\hat{Bags}_t = \beta_0 + \beta_1 treatment_t + \beta_2 clients_t + \beta_3 revenues_t \tag{1.2}$$

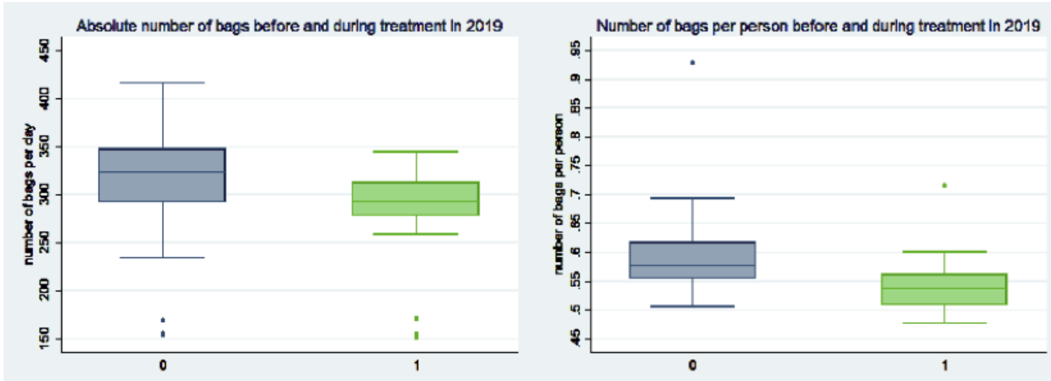

Figure 1.3: Total number of bags per day and number of bags per person before and after the treatment (2019 control period)

$$\hat{Bags}_t = \beta_0 + \beta_1 treatment_t + \beta_2 clients_t + \beta_3 revenues_t + \beta_4 revenuesppt \tag{1.3}$$

$$\hat{Bagsspp}_t = \beta_0 + \beta_1 treatment_t + \beta_2 clients_t \tag{1.4}$$

$$\hat{Bagsspp}_t = \beta_0 + \beta_1 treatment_t + \beta_2 clients_t + \beta_3 revenues_t \tag{1.5}$$

$$\hat{Bagsspp}_t = \beta_0 + \beta_1 treatment_t + \beta_2 clients_t + \beta_3 revenues_t + \beta_4 revenuesppt \tag{1.6}$$

Where $Bags_t$ is the absolute number of bags sold on day t, treatment is a binary variable taking value 1 in the days of treatment (June 23rd 2019 to 14 July 2019), $clients_t$ is the number of receipts on any given day, which is a proxy for the number of clients who visited the store. $revenues_t$ is a variable with the revenues (in euro) for any given day and $revenuespp_t$ is computed by taking the ratio between $revenues_t$ and $clients_t$. Finally $Bagspp_t$ is a variable obtained by dividing $Bags_t$ by $clients_t$ and is a measure of the average amount of bags per client.

We observe that the treatment is significant in all the specifications, but the effect is slightly smaller than that indicated by the difference in means for the total amount of bags (Table 1.3). However, we still observe a drop of around 8% in the daily number of bags used. Notably, the effect of the treatment is robust to our controls (number of clients, revenues and revenues per person) and it does not vary much in size between specifications.

As predictable, there is a strong and positive relationship between the bags consumed and the revenues and number of clients. To account for this, the third and sixth specification also control for revenues per person. In both specifications the coefficient of the revenues per person is significant and positive, highlighting that customers that spend more are likely to purchase more bags.

	bags_2019	bags_2019	bags_2019	bagspp_2019	bagspp_2019	bagspp_2019
	(1)	(2)	(3)	(4)	(5)	(6)
treatment	-27.78***	-26.65***	-27.14***	-0.0581**	-0.0558***	-0.0579***
	(7.395)	(6.026)	(5.644)	(0.0177)	(0.0154)	(0.0119)
clients	0.458***	0.247***	0.713***	-0.000393***	-0.000829***	0.00117**
	(0.0319)	(0.0530)	(0.191)	(0.0000763)	(0.000135)	(0.000403)
revenues		0.0167***	-0.0300		0.0000345***	-0.000166***
		(0.00365)	(0.0188)		(0.00000930)	(0.0000396)
revpp			27.65*			0.119***
			(10.96)			(0.0231)
constant	68.10***	82.40***	-193.7	0.807***	0.836***	-0.350
	(17.74)	(14.78)	(110.3)	(0.0424)	(0.0377)	(0.233)
Observations	42	42	42	42	42	42
adj. R^2	0.845	0.897	0.910	0.453	0.588	0.753

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.3: Estimates (unstandardized β slopes) of the determinants of bags consumption in 2019 with standard errors in parentheses.

1.4.3 Difference-in-Differences

As Rivers et al. (2017) note, a simple regression might lead to an overestimation of the effect of the treatment. To avoid this, we run a difference-in-differences specification. Here we consider the data from the year 2018 in the treated store as if it was a different store. In 2019 we divide the two periods (before the treatment and during the treatment) as the three weeks ranging from May 20th, 2019 to June 9th, 2019 (control-2019) and June 23rd, 2019 to 14 July 2019 (treatment-2019). For the 2018 we consider as untreated the three weeks between May 21st, 2018 and June 10th, 2018 and use the weeks from June 25th, 2018 to July 15th, 2018 as a comparison with the treated weeks in 2019. This corresponds to the third dataset described above. Although the data shows some seasonality and bags' sales oscillate in different days of the week, the parallel trends assumption seems to hold and hence inference is possible from this identification.

The difference-in-differences design allows us to capture the overall trend in the consumption of bags and disentangle the effect of the treatment. Difference-in-differences accounts for all time-invariant differences between 2018 and 2019, however it does not account for factors that can change over time. Therefore, as the daily revenues and the number of clients vary over time, we run two further specifications where we control for clients and revenues.

We find that in all the difference-in-differences specifications except the first for the total number of bags (where we do not control for clients or revenues) the effect of the treatment is

	bags	bags	bags	bagspp	bagspp	bagspp
	(1)	(2)	(3)	(4)	(5)	(6)
difference	-35.05	-43.19**	-41.50***	-0.0997**	-0.0930**	-0.0898***
	(-1.19)	(-3.34)	(-3.58)	(-2.84)	(-3.35)	(-3.52)
clients		0.486***	0.304***		-0.000398***	-0.000741***
		(18.35)	(6.58)		(-7.01)	(-7.26)
revenues			0.0151***			0.0000285***
			(4.57)			(3.91)
constant	336.3***	63.93***	76.93***	0.607***	0.830***	0.854***
	(22.80)	(3.95)	(5.21)	(34.60)	(23.92)	(26.26)
N	84	84	84	84	84	84

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.4: Difference-in-differences estimates for daily bags and bags per person between 2019 and 2018

negative and statistically significant (Table 1.4). Both factors are statistically significant and controlling for them reinforces the effect of the treatment. The treatment effect revealed by the difference-in-differences is a drop of around 13% (taking the impact of the treatment to be the one from column (3)) with respect to the average number of bags in the control-2019 and 12% in the number of bags per person with respect to 2018. Thus, unlike Rivers et al. (2017), we observe a stronger effect when using the difference-in-differences specification. Consequently, not controlling for clients and revenues would bias the results and understate the effect of the treatment. Moreover, the changes in social norms are not sufficient to explain the lower use of bags during the treatment weeks.

Overall, we find support for our hypotheses: we observe a lower number of bags used (both in absolute terms and per person) during the treatment period. All the different specifications (difference in means, regressions and difference-in-differences) show a highly statistically significant difference in the number of bags consumed before and during the treatment period.

1.4.4 Persistence of results

Last, we test whether the results of the treatment are persistent. That is, whether the consumption of biodegradable bags remains lower than during the pre-treatment period also when the treatment is concluded. We start by comparing the control-2019 period with the post-treatment week. We observe that in the post-treatment week the number of bags

	(Persistence)				
	Treatment (mean)	Post-Treatment (mean)	Diff.	Std. Error	Obs.
bags	279.1429	222.4286	-56.7143**	22.5740	28
bagspp	0.5437	0.4649	-0.0788***	0.0268	28
	No treatment (mean)	Post-Treatment (mean)	Diff.	Std. Error	Obs.
bags	311.3333	222.4286	-88.9048***	25.9227	28
bagspp	0.5980	0.4649	-0.1332***	0.0381	28

Table 1.5: The table shows the average amount of daily bags purchased during the treatment and after the treatment (top panel), and before the treatment and after the treatment. The difference between the post-treatment period and previous ones is reported with standard errors and number of observations used for the test.

and the number of bags per person is significantly lower both than the control period and the treatment period (Table 1.5). This result holds also when controlling for the number of clients and revenues.

This is an important result, since nudges effects rarely persist (Brandon et al., 2017). However, we acknowledge that persistence should be tested over a longer time horizon.

1.5 Discussion

The main finding of our experiment is that nudge based on a carefully chosen combination of charity and anti-charity can lead to a significant reduction in the consumption of carrier bags and incentivises people to bring their own reusable bag from home. We do not claim that this specific combination of charity and anti-charity holds any special value, or that it is the most effective. On the contrary, we suggest that any suitable choice of charity and anti-charity can induce pro-environmental behaviour. Consequently, we invite policymakers to consider preferences that are geographically homogeneous across demographic groups when devising nudges of this kind. The questions that remains open concern the external validity of our findings, and more precisely whether a similar nudge would work elsewhere. We now turn to answering this question.

1.5.1 External Validity

To begin with, we remark that we attain our results in a real-world scenario, hence we can observe real data on disposable bags consumption, instead of just self-reported behaviour (Rivers et al., 2017). Moreover, we collect a much larger number of observations over a much longer time interval than comparable studies carried out in a real-world scenario, e.g., Rubens et al. (2015). These are fundamental advantages in this context. In fact, one of the main problems faced when attempting to reduce carrier bags consumption is that people tend forget to bring their own bag from home (Musa et al., 2013; Zen et al., 2013; Bartolotta and Hardy, 2018). Thus, an effective treatment should influence a behaviour - remembering one's own bag - that happens many days later and in a different location (generally the home of the consumers). Testing whether a treatment can achieve this goal in a study carried over a single day, e.g., Rubens et al. (2015), is problematic. For these reasons, an experiment that is carried out in a real-world context over a relatively long time has a comparatively high external validity. Additionally, it is important to note that the experiment was carried out at the end of the 2018/2019 season, and hence no important matches were played during the treatment. It would be interesting to test how competitive matches mediate the effect of the treatment on the consumption of single use bags. One reasonable hypothesis is that important matches would increase the salience of the treatment and consequently strengthen its effect on customers' behaviour.

1.5.2 Implementing the nudge

The fundamental problems that policymakers face when implementing any regulation are asymmetric information and imperfect enforcement. The regulated generally know much better than the regulator the environment to which the regulation applies and monitoring the behaviour of the regulated is costly and often unfeasible. In this context a first challenge for the regulator would be identifying the optimal disposition of the large and the small posters in each supermarket in which the regulation is implemented. Another challenge would be ensuring that supermarket owners do not move or remove the posters when they are not monitored. Normally these would be insurmountable obstacles as people and store owners often do not comply with regulations that attempt to incentivise pro-social behaviours. However, thanks to place attachment and sport preferences, our treatment created a diametrically opposite dynamic. On the first day, we placed the poster at the entrance of the supermarket since we believed that it was the most visible place. Two days later, we found that one of the cashiers moved it behind the cash registers. He gave us two reasons. First, he argued that in this way they could rely on the information provided by the poster when explaining the experiment to the customers. Second, he noted that customers spend much more time waiting at the cashier than at the entrance of the supermarket, and hence placing the poster by the cashier would give the customers more time to read the details of the experiment. While we have no practical way of testing whether he was correct, his suggestion was reasonable and was clearly an attempt to improve the treatment. To put it differently, it was the regulated (i.e., the cashier) that attempted to identify the optimal place for the poster in order to make the regulation (i.e., the treatment) more effective. This attention on how to improve the regulation suggests also that the need to monitor compliance is minimal, since ensuring that the charity wins over the anti-charity seems to be in the interest of the regulated. Although we cannot be certain that the same dynamic will emerge if the treatment is replicated elsewhere, it is reasonable to expect that this might be the case. Cashiers are also likely to be from the area in which the supermarket is located, and hence to share the same sport preferences as the customers.

Moreover, while effective, our treatment is cheap and not invasive. Scholars like Rubens et al. (2015) rely on interventions that require one-on-one interactions with the customers of the supermarket. However, implementing on a large scale this kind of treatment would be extremely costly for the regulators, while customers might be upset by such invasive treatment. On the contrary, our treatment can be conducted at a low cost even on a large scale and minimises the interference with customers' grocery experience. To this, one could object that if the treatment is implemented on a large scale the system of donations might become expensive. However, regulators can address this problem without weakening the impact of the treatment. As noted above, we did not use Juventus itself as an anti-charity because for us it was less problematic to arrange donations to an ONLUS. However, policymakers can involve the charities and the anti-charities in their regulations. For instance, assume that New York and Boston wanted to implement a nudge of this kind to reduce the consumption of carrier bags. An intriguing possibility would be involving directly the New York Yankees and the Boston Red Sox. First, the two teams could pool a certain amount of money (e.g., $100.000 each). Then, the cities of Boston and New York would implement the treatment in all the supermarkets of the two cities. At the end of the treatment period one would compare the reduction in carrier bags in the two cities to determine which team has won and should collect the pooled money. For example, if the treatment proves to be more effective in New York, then the Yankees would get the $200.000 jackpot. Assuming that they have the same probability of winning, the expected value for the Yankees and the Red Sox of participating in this treatment would be zero. The winning team could either use the money to buy better players or donate to charities chosen by its supporters. Since the teams would certainly increase their salience in the mind of the people, it is likely that they would be willing to become involved in projects of this kind (provided that they do not have to set up the treatment themselves). At the same time, since the prize does not come from donations but from the "charities" themselves, regulators can implement this policy at virtually no cost. These city-wide events are likely to lead to more engagement from citizens and to increase awareness on the problems caused by single-use carrier bags. In implementing the treatment we faced one problem. In particular, we observed that the amount we found in the buckets not always matched the actual data on biodegradable bags consumption. In particular, during the first week of the treatment too much was being donated to the good charity in relation to the consumption of biodegradable bags. It is only after we reiterated to the cashiers of the supermarket that we could cross check the data on single-use carrier bags sold and the amount of money in the two buckets that donations started to reflect biodegradable bags consumption more accurately. This is due to an obvious problem: just like the customers, the cashiers are also likely to support the local team and to despise the rival team. However, if they donate to the good charity also when the costumers do not have the biodegradable bag, the effect of the nudge disappears. For this reason, it is important that the cashiers are made aware that the actual consumption of biodegradable bags can be checked. Moreover, if a regulator intends to implement this nudge, it should consider including some monetary rewards for cashiers that carry out the treatment properly. That is, those cashiers for which the amount of money in each bucket is consistent with the observed data on single-use carrier bags consumption.

In order to apply the nudge in different contexts, it is necessary to adopt suitable charities and anti-charities. While Juventus was effective as an anti-charity in Napoli, it is unlikely to work in a city in United States or in China. Therefore, regulators should ensure that the choice of the charity and the anti-charity is based on the preferences of the people that shop in the area where the treatment will be implemented. On the bright side, sport rivalries tend to be significant and geographically homogeneous around the globe. Most Indians would probably go out of their way to avoid helping the Pakistani cricket team, and vice versa (Lavalette, 2019). Similarly, New Zealand supporters might be induced to bring a plastic bag if the impending threat is contributing to Australian rugby or cricket team (New Zealand Herald, 2016). Therefore, it is likely that the results of this experiment can be replicated in various countries.

The keys to implement nudges of the kind proposed in this article are creativity and knowledge of the social context in which the treatment will be implemented. For example, professional sport teams might not always be the best option. Consider the case of the Italian city of Siena. In this city there is a strongly felt rivalry among "contrade" (similar to neighbourhoods) that culminates every year in the world-wide famous Palio di Siena. A system of donations that would reward the contrada that reduces the most the consumption of carrier bags is likely to be extremely effective. Moreover, these kinds of nudges can be exploited also in different contexts. For instance, a number of studies suggest that it is possible to induce pro-environmental behaviour by relying on that social comparison messages (Ferraro and Price, 2013). We argue that this effect could be further enhanced by relying on inter-group dynamics. For instance, a policymaker could start a competition between citizens of two different areas in which two rival teams are popular (e.g., Madrid and Barcelona): The area in which the consumption of electricity decreases more will win the competition. We argue that connecting such initiative to highly salient charities and anti-charities like sport teams would significantly increase their impact.

1.6 Conclusion

Reducing the consumption of carrier bags is an important step to protect the environment. However, traditional approaches like outright bans and taxes have only had a limited impact. For this reason, policymakers should explore new solutions to address this problem and to induce people to bring their own bag from home when they go to supermarket. To this end, we proposed an innovative form of nudge that builds on sport preferences. The mechanism is very simple to understand for supermarket customers and very easy to implement for policymakers. When a customer has her own bag, and hence is not purchasing an additional bag in store, a small donation is made to a charity that is likely to be perceived positively by the supermarket customers. Vice versa, when the customer purchases the bag in store a small donation is made to a charity that is likely to be disliked by the supermarket customers (anti-charity). For this experiment we selected Juventus as anti-charity, as it is disliked by most people in the area in which the experiment is carried out. This treatment imposes no additional costs on consumers. We also explain how to carry it out at virtually no cost for policymakers. We find that this nudge resulted in a significant decrease in both the total number of carrier bags and the bags per-capita purchased in the treated supermarket. Moreover, the effects of the nudge persisted also after the treatment is over, which suggests that it might have a long-lasting impact.

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1.A Appendix

Here we present the results of difference in means, regressions and difference-in-differences when including the two transition weeks in the treatment. The difference in means test shows that, while clients and revenues are not statistically different between the two periods, the consumption of bags per person is lower in the treatment period. The full results of these tests are presented in Table 1.A.1.

Differences in means for daily bags and bags per person purchased					
	No treatment(mean)	Treatment (mean)	Difference	Std. Error	Obs.
clients	527.3462	529.7714	2.4253	31.4648	61
revenues	5869.2235	5751.4486	-117.7749	454.9179	61
bags	306.1923	279.9714	-26.2209	15.9658	61
bagspp	0.5932	0.5415	-0.0517**	0.0230	61

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.A.1: Difference in means for bags per day and bags per person (bagspp) before and after the treatment considering 5 weeks of treatment (2019 control period).

We proceed, as in the Statistical Analysis section, by looking at the regressions controlling for clients (1, 4), clients and revenues (2, 5) and clients, revenues and revenues per person (3, 6) as determinants for the total amount of bags sold (1, 2 and 3) and the bags per person (4, 5 and 6). We find that the treatment is statistically significant in all the specifications, reinforcing our belief that people started changing their behaviour once they learned about the treatment. We further investigate the impact of the treatment by looking at the difference-in-differences specifications and considering the five weeks as treatment. The results remain statistically significant for the same specifications.

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	(1)	(2)	(3)	(4)	(5)	(6)
	bags	bags	bags	bagspp	bagspp	bagspp
treat	-27.23**	-23.85**	-25.50***	-0.0505**	-0.0442**	-0.0508***
	(8.790)	(7.154)	(7.010)	(0.0175)	(0.0146)	(0.0127)
clients	0.415***	0.134*	0.649*	-0.000487***	-0.00101***	0.00105*
	(0.0368)	(0.0585)	(0.258)	(0.0000732)	(0.000120)	(0.000470)
revenues		0.0229***	-0.0278		0.0000430***	-0.000160***
		(0.00410)	(0.0252)		(0.00000840)	(0.0000457)
revpp			29.85*			0.120***
			(14.61)			(0.0266)
constant	87.54***	101.0***	-200.6	0.850***	0.875***	-0.333
	(20.53)	(16.82)	(148.6)	(0.0408)	(0.0344)	(0.270)
N	61	61	61	61	61	61
adj. R^2	0.690	0.796	0.807	0.460	0.623	0.719

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.A.2: Estimates (unstandardized β slopes) of the determinants of bags consumption in 2019 with standard errors in parentheses considering 5 weeks of treatment.

	bags	bags	bags	bagspp	bagspp	bagspp
	(1)	(2)	(3)	(4)	(5)	(6)
difference	-40.22	-47.51***	-44.51***	-0.0985**	-0.0918***	-0.0865***
	(-1.51)	(-3.54)	(-3.90)	(-2.93)	(-3.48)	(-3.73)
clients		0.470***	0.232***		-0.000429***	-0.000854***
		(17.80)	(5.40)		(-8.27)	(-9.79)
revenues			0.0203***			0.0000361***
			(6.51)			(5.71)
constant	336.3***	72.65***	87.11***	0.607***	0.848***	0.873***
	(22.63)	(4.38)	(6.10)	(32.32)	(25.98)	(30.09)
N	112	112	112	112	112	112

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.A.3: Difference-in-differences estimates for daily bags and bags per person between 2019 and 2018 considering 5 weeks of treatment.

Chapter 2

Climate visuals: The Effect of Colours on Understanding, Concerns and Policy Preferences

2.1 Introduction

Between 2021 and 2022 the Intergovernmental Panel on Climate Change (IPCC) has released its Sixth Report, which indicates that the earth is warmer than it has been in 125,000 years (Tollefson et al., 2021). The report stresses that human influence on the atmosphere, ocean and land is "unequivocal" (Masson-Delmotte et al., 2021), and that "human-induced climate change [...] has caused widespread adverse impacts and related losses and damages to nature and people". In 2018, the IPCC had already stated that the world had to take drastic actions to prevent the catastrophic consequences associated with global warming (Tollefson, 2018). And yet, relatively little has been done. Policy responses have thus far had a very limited impact (Green, 2021), and in countries like U.S. a large part of the adult population still does not always act in a way that helps protecting the environment (Duan and Bombara, 2022). It is thus imperative that the message of the Sixth IPCC Report reaches a wide audience to improve the understanding of the climate crisis and to increase the support for climate mitigation policies.

Previous literature has studied whether the information contained in the previous IPCC Reports is presented in a clear and effective manner, but most of the studies have focused on text readability (Barkemeyer et al., 2016). However, in a world in which people are exposed to large amounts of information, climate visuals play a key role (Harold et al., 2016). Visuals can present and summarise large amounts of complex information (Wardekker et al., 2008) and potentially promote engagement with environmental issues (Smith and Joffe, 2009). Moreover, visuals can invoke emotional responses (Smith and Joffe, 2009), and research has shown that emotions can help creating support for policies aimed at limiting climate change disruptions (Nabi et al., 2018). Carefully crafted visuals might even contribute to reducing the perceived psychological distance of climate change (Brügger et al., 2015), which in turn might foster pro-environmental behaviours (Jones et al., 2017).

However, using visuals to convey complex scientific information in an understandable and not misleading manner is complicated (McMahon et al., 2015; Morelli et al., 2021), especially given that large parts of the world population have low graph literacy (Maes, 2017). Moreover, the specialists who worked on the figures of the SPM noted that "there are a number of distinct challenges to creating visuals for IPCC [Summary for Policymakers]. Among other requirements, visuals need to be scientifically rigorous, explain scientific assessment and often integrate several lines of evidence while also being transparent and relevant for a growing mix of users" (Morelli et al., 2021).

A crucial component of climate visualisation is colour (Morelli et al., 2021). Colours are a highly salient characteristic of any visual, and previous literature has highlighted how they can aid or hinder graph understanding (Teuling et al., 2011; Retchless and Brewer, 2016). However, it is still unclear whether the choice of colours in climate visualisation affects the support for policies aimed at mitigating global warming and if it affects the emotional response to climate-related information. We investigate these questions by carrying out two experiments with large representative samples of U.S. residents (N = 1000 in each experiment). The first experiment investigates role played by colours in a visual used in the Summary for Policymakers (SPM) of the Physical Science Basis (PSB) report of the IPCC (see Figure 2.1, left panel). The second experiment focuses on the choice of colours made by the Financial Times (FT) when using a visual taken from the IPCC Report (see Figure 2.2, left panel). In fact, many newspapers included visuals from the IPCC SPM in their articles, but sometimes they changed the colours used in them (see Table 2.1 for a list of newspaper that used IPCC visuals with different colours). Thus, in light of the fact that most people are likely to learn about the content of the IPCC Reports from the media, we investigate the role played by this editorial choice.

At the general level, we find that colours have limited impact when considering the overall sample. Our most interesting finding is that merely altering the colours used in a visual related to climate change can improve Republicans' understanding of the climate visual and affect their support for climate related policies. The fact that colours can have an impact on Republicans is an important insight and was worth investigating for two reasons. First, generally Republicans tend to be less in favour of policies addressing global warming, but comprehensive reforms need bi-partisan support (Bernauer and McGrath, 2016; Ehret, 2021). Second, given that Democrats already tend to be aware of the severity of the climate crisis there might be a ceiling effect, and hence the treatment tested would be unable to further increase the support for climate policies among this group. In fact, we do observe a very high baseline support for climate mitigation policies among non-Republican respondents.

Last, contrarily to the prediction of the literature, e.g., Terrado et al. (2022), we observe that ignoring standard symbolism does not lower comprehension of climate visuals. For instance, the choice of the Financial Times to use blue to describe the warmest and worst scenario in a climate visual did not affect negatively respondents' understanding of the visual.

One important caveat, however, is that visuals have many components which are likely to interact with each other in ways that existing evidence does not allow one to predict. Thus, it is impossible to predict whether similar treatment would have the same impact when considering different visuals. However, our findings do allow us to establish that: *i*) colours *can* influence support for climate mitigation policies among Republicans; and *ii*) using colours that ignore standard symbolism *do not necessarily* worsens graph comprehension.

2.2 Literature review

2.2.1 Climate change and polarisation

Climate change discussions in the United States remain highly partisan (Bayes and Druckman, 2021). While in recent years the number of Democrats that recognises the seriousness of the climate crisis and acknowledges the need to act to prevent global warming's most catastrophic consequences, many Republicans remain sceptical. And yet, without broad bipartisan support it will be hard to pass comprehensive and effective reforms addressing the climate crisis (Bernauer and McGrath, 2016; Ehret, 2021).

For this reason, scholars started investigating how to frame climate-related messages in order to reach a sufficiently large fraction of the population. While some of these studies have revealed that framing can be effective to a certain extent (Buchanan et al., 2022; Scannell and Gifford, 2013), others found either no effect (Bernauer and McGrath, 2016) or that the effect can easily by neutralised by counter frames (Aklin and Urpelainen, 2013; McCright et al., 2016). One possible explanation for the finding that framing is not always effective is that climate change is a highly polarised and debated topic, and hence people are likely to have been exposed to information and partisan cues (Goldberg et al., 2021).

To put it differently, they are "pre-treated" before any experiment (Bernauer and McGrath, 2016).

More worryingly, some studies have found evidence that framing can backfire and trigger reactance (Zhou, 2016; Ma et al., 2019; Chan and Lin, 2022; Chinn and Hart, 2021). Reactance can be defined as an "oppositional response to perceived pressure for change that occurs when a person believes that a message threatens his or her agency or freedom" (Nisbet et al., 2015). Given that conservatives tend to be wary of laws restricting individual freedoms, they are more likely to be prone to exhibit reactance in the context of climate regulation (Irmak et al., 2020; Chan and Lin, 2022). For instance, Chinn and Hart (2021) find that climate change consensus messages trigger reactance among Republicans. Similarly, Ma et al. (2019) observe that emphasising the scientific consensus on climate change can trigger reactance among people who question the existence of climate change. Generally, the literature found that reactance is more likely to be triggered when the framing involves particularly assertive language or persuasive messages with an explicit intent (Ma et al., 2019). As colour-based framings of climate related visuals do not present these features, it is important to investigate whether they can foster understanding of the climate crisis and can affect policy preferences, especially among Republicans.

2.2.2 Climate visualisation

Visuals play a key role in communicating climate information (Calvo et al., 2022; Terrado et al., 2022). This is because "data visualisation harnesses the human visual system's capacity to be a powerful pattern detector. Data presented in visual forms can aid decision-making when it leverages our remarkable ability to process visual information" (Morelli et al., 2021). However, finding the right way to leverage the potential of data visualisation is complex. Most of the existing ways of depicting data are based on the premise that the target audience is formed by experts, and thus might not be suitable to communicate to a larger audience (Grainger et al., 2016; Terrado et al., 2022). As a result, scientists often feel that their messages are ignored, whereas non-scientists complain that the information is not presented in formats that meet their needs (Grainger et al., 2016).

A burgeoning literature is attempting to improve the state of the art by trying to identify new and more effective ways to represent data and by comparing different ways of visualising information (Daron, Lorenz, Wolski et al., 2015; Daron, Lorenz, Taylor et al., 2021; Christel et al., 2018), but there is still much to be learnt.

The IPCC has acknowledged the importance of visuals, as highlighted by the committee's decision to invite information designers to be lead authors of its report. Notably, these experts have flagged colours as one of the key factors to guide the user in the experience of processing information together with space, layout, typography and annotations (Morelli et al., 2021). Moreover, the IPCC has issued a detailed visual style guide for authors, in order to ensure that all visuals meet certain standards, and a large portion of the guidelines deals with the way in which colours should be used in climate visuals. For these reasons, in our first experiment we analyse the role of colours in IPCC climate visuals, and in particular SPM.3 (Figure 2.1). The importance of visuals is further underscored by the fact that many of the newspapers that reported on the content of the IPCC Report included in their articles the visuals that were used in the SPM. This is especially relevant because it is reasonable to assume that most people learn about the content of the IPCC Report from media, instead of directly reading the report. In some instances, however, major newspapers have changed the colours used in the IPCC visuals, sometimes selecting colours that are counter-intuitive. Thus, in our second experiment we investigate the impact of this editorial choice of changing the colours of IPCC visuals.

2.2.3 The role of colours

Colours are a a key variable in visuals because they can be combined with other visual mappings without taking up additional space on a page (Bernard et al., 2015). Colours are usually represented using one of the many existing colour spaces (e.g., RGB, HSV, CIE Lab, Munsell, etc.). For instance, in the RGB space colours are described by a set of red, green and blue coordinates ranging from 0 and 255.

With respect to climate visualisation, the research on colours has largely focused on how to convey uncertainty (Retchless and Brewer, 2016; Grigoryan and Rheingans, 2004; Viard et al., 2011) and how to identify the best colour scale in quantitative mapping (**harrower2003colourbrewer**; Brewer et al., 1997; Dasgupta et al., 2018). However, more research is needed on the role of colours in climate visuals.

For instance, more research is needed to understand the impact of semantic discriminability, which is defined to be "the degree to which observers can infer a unique mapping between visual features and concepts, based on the visual features and concepts alone" (Schloss et al., 2020). To put it differently, some colours might more naturally evoke certain concepts associated with climate change. For instance, people might naturally associate red with high temperatures and extreme risk, whereas blue might be associated with low temperatures and best case scenarios (Schneider and Nocke, 2018). Scholars have hypothesised that visuals adopting colours with low semantic discriminability hinder understanding (Terrado et al., 2022). In our experiments we test whether this hypothesis is true.

But colours are not only important because they can aid or hinder understanding. They can also evoke emotions (Valdez and Mehrabian, 1994; Kaya and Epps, 2004), which might shape the reaction to the visual. Ultimately, like other components of visuals (Romano et al., 2020), colours might impact policy preferences and beliefs. Scholars have not yet investigated this possibility, and in this study we attempt to fill this gap.

2.3 Hypotheses development

We designed two small scale studies (N = 100 and N = 50) to identify the associations between the colours in the visuals used in our experimental manipulations and words related with climate change. This provided us with information on the semantic discriminability of the colours used in the various visuals. Moreover, we carried out two experiments with two large representative samples of the U.S. population (N = 1000 for each experiment) to study the impact of colours on participants' policy preferences, concerns for global warming and understanding of climate visuals. The first small study and the two large scale studies were pre-registered with AsPredicted (Small study, Study I, Study II).

In the small studies we elicit participant's associations between colours and a number of concepts, e.g., "best-case scenario", "extreme cold".

In our first experiment, we focus on the figure SPM.3 of the IPCC Report. The figure is composed of three panels (see Figure 2.1, left panel). The top panel describes observed changes in hot extremes, with increases marked in red and decreases marked in blue. The middle panel describes observed changes in heavy precipitations with increases marked in green and decreases marked in yellow. Last, the bottom panel describes observed changes in agricultural and ecological drought with increases marked in yellow and decreases marked in green.

Two things are worth noting. First, the colours used in the middle and the bottom panel have low semantic discriminability. In particular, the middle panel shows bad outcomes in green, a colour that generally has a positive connotation in connection with the environment. Second, different colours are used to mark positive and negative events within the same figure.[1] In this study, the experimental manipulation was to mark in all three panels

[1] One explanation for the colours used in SPM.3 could be that the authors decided on the basis of consistency among the graphs that appear in the IPCC Report. In fact, the Visual Style Guide for Authors of the IPCC suggests to use consistent colour scales. However, the colours used in the Figure SPM.3 are different

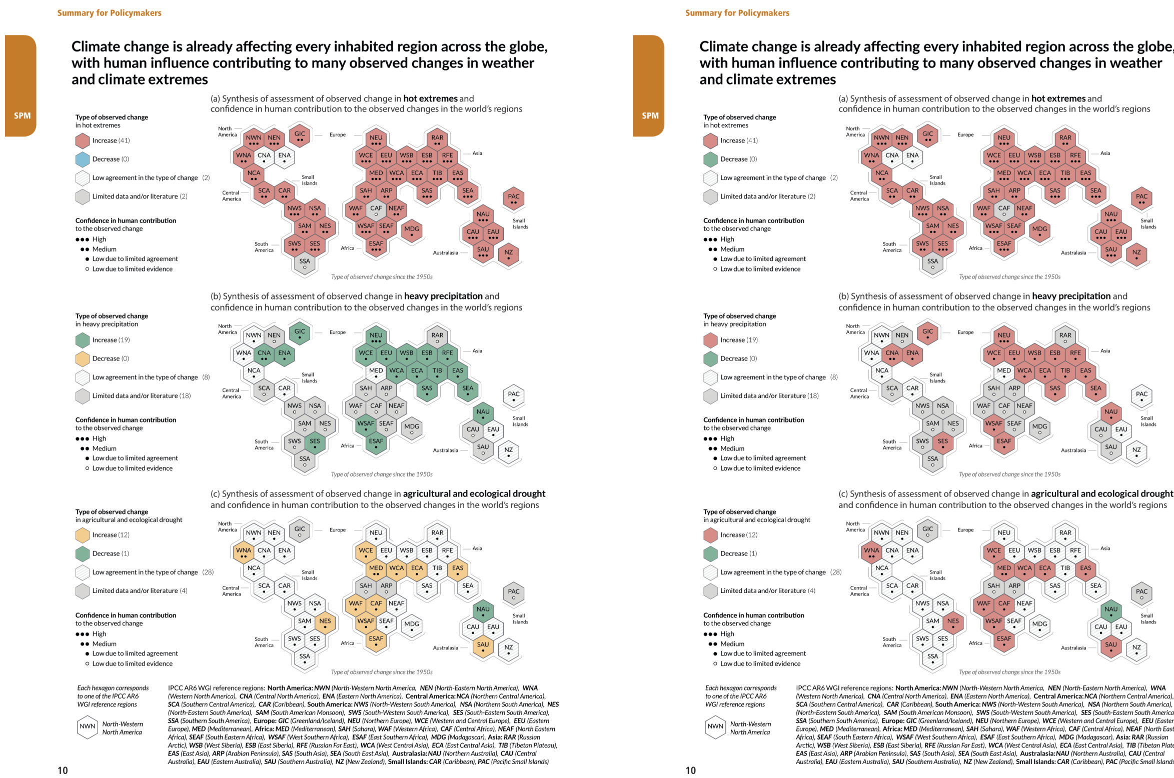

Figure 2.1: The left panel represents Figure SPM.3 as it appears in the IPCC Report. The right panel represents our treatment.

negative changes (increases in hot extremes, in heavy precipitations and in agricultural and ecological droughts) in red and positive changes (decreases in hot extremes, in heavy precipitations and in agricultural and ecological droughts) in green. This change increased both semantic discriminability and the internal consistency of the graph, given that all negative events became associated with red. These two facts might improve participants' comprehension of the figure. Moreover, by increasing the overall amount of red in the figure, our experimental manipulation might make the figure look more threatening, which in turn would increase the level of concern for climate change and the support for climate change policy. Therefore we formulate the following hypotheses:

- H1a A consistent use of colours within a graph can foster understanding, which in turn can increase support for policies aimed at mitigating climate change.
- H1b The use of colours generally associated with risk and negative outcomes like red can increase the level of concern for climate change, which in turn can increase support for policies aimed at mitigating climate change.

Turning to the second experiment, a leading newspaper like the Financial Times provided us with a great opportunity to study the role of semantic discriminability in a setting with real world implications. The main panel of the SPM.4 Figure of the SPM of the first part of the IPCC Report describes five possible scenarios in terms of future CO_2 emissions (Figure 2.2, right panel). Consistently with suggestions from the literature, the curve describing the worst case scenario is in dark red, whereas the curve describing the best case scenario is in light blue. In one of its articles, the Financial Times included a figure that is almost identical, but it changed the colours of the curves (Figure 2.2, left panel). For instance, the curve describing the best case scenario is in light blue, whereas the curve describing the worst case scenario is in pink. Our surveys confirmed that the colours used by the IPCC have higher semantic discriminability. For worst case scenarios, on a scale from 1 to 10 respondents associated the dark red used by the IPCC more strongly with both "worst case scenarios" (4.88) and "great risk" (5.42) than the colour used by the FT (1.72 and 1.85, respectively). Similarly, for the best case scenario, the light blue used by the IPCC was more strongly associated with "best case scenarios" (5.06) than the colour used by the FT (3.08).

The Financial Times was not the only newspaper to deviate from the colour combinations adopted by the IPCC (see Table 2.1).

from both the colours used in the Visual Style Guide for Authors and the colours used in other graphs of the IPCC Report (e.g., SPM 5(c) and SPM 6 use different colours from SPM.3 to describe increases in precipitations).

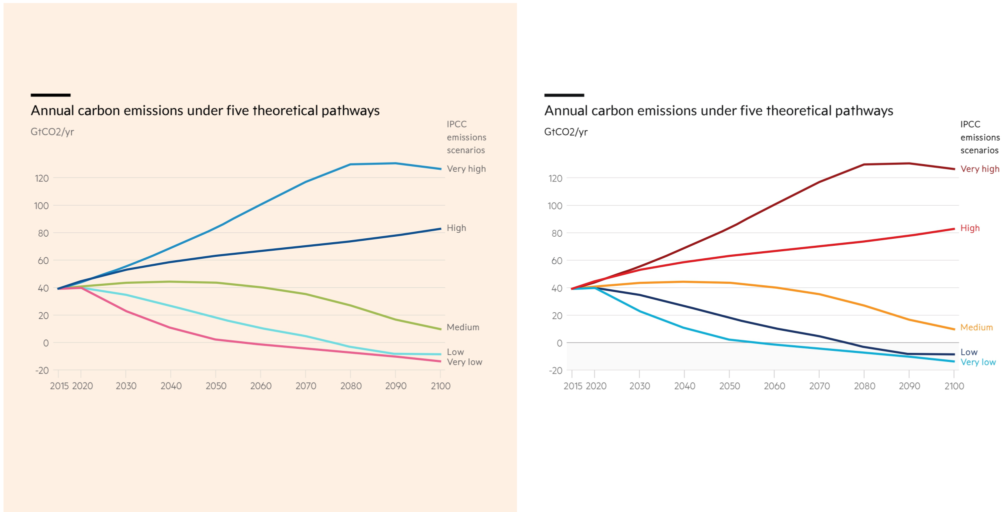

Figure 2.2: The left panel represents Figure SPM.4 as it appears in the Financial Times. The right panel represents our treatment, in which we used the colours of the IPCC report.

Newspaper	**Country**	**Date**	**Figure**
BBC	UK	9-8-21	SPM.8 (panel d)
Bloomberg	UK	9-8-21	SPM.1, SPM.3, SPM. 4 (panel a)
CNN	US	9-8-21	SPM.4 (main panel)
Eos	US	9-8-21	SPM.1 (left panel), SPM.4 (panel a) SPM.8 (panel a)
NBC	US	9-8-21	SPM.6 (bottom right panel)
Straits Times	Singapore	9-8-21	SPM.4 (main panel)
Suddeutsche Zeitung	Germany	9-8-21	SPM.1 (right panel), SPM.8 (panel a)
The Guardian	UK	9-8-21	SPM.1 (right panel)

Table 2.1: A list of major newspapers from around the globe that included in their articles figures taken from the IPCC Report, but that changed the colours used in the figures.

In most of the instances in which newspapers deviated from the colour choice of the IPCC, they have selected colours that seem to have lower semantic discriminability. Considering that people are more likely to learn about the findings of the IPCC from media like newspapers than from the original report, it is important to understand whether the choice of colours affects understanding. Thus, in our second study, our experimental manipulation is to show the Financial Times graph, but with the high semantic discriminability colours used in the IPCC report. We formulate the following hypothesis:

H2 Using colours with low semantic discriminability reduces graph comprehension.

2.4 Methods

2.4.1 Colours and semantic discriminability

To have a precise measure of the semantic discriminability of the colours that appear in the figures used in our studies, we launched two smaller surveys. In total, we recruited 150 U.S. residents on Prolific.co, a platform widely used for this kind of studies (Bugden, 2022; Tam et al., 2022). Respondents were paid \$0.55 (hourly compensation \$6.6). In this survey, all participants were shown the colour palettes used by the graphs on which study 1 and study 2 focus. In total, each respondent saw 16 palettes. For each palette, the respondents where asked to indicate the level of pleasure and the level of arousal that they felt when seeing the colour. The questions were asked using the validated self-assessment scale introduced in Betella and Verschure (2016). Moreover, for each palette respondents were asked to indicate how strongly they associated each colour with the following words: extreme cold, extreme heat, heavy precipitations, droughts and climate crisis. The second survey had an identical structure, but it asked respondents to associate each colour with the following words: maximum values, great risk, worst-case scenario, anomalies, best-case scenario.

2.4.2 Study I

Visual and experimental manipulation

Our experimental manipulation in study I related with the main panel of the SPM.3 figure of the SPM of the first part of the IPCC Report. Half of the respondents were randomly assigned to seeing the original colours from the IPCC Report, the other half was randomly assigned to see a figure in which all the increases of extreme events were marked in red and the decreases in green (see Figure 2.1). Figure 2.3 summarizes the flow of Study I.

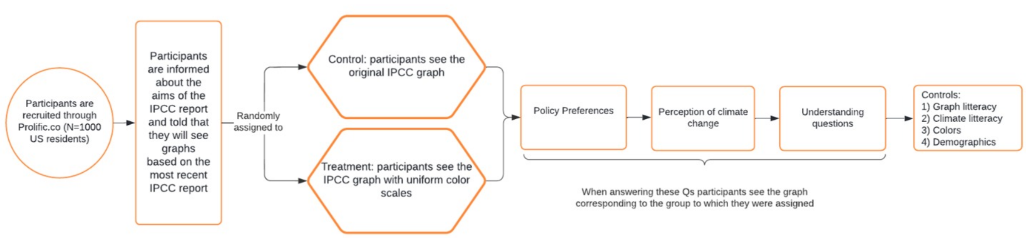

Figure 2.3: Flow of Study I

Question	Range
Support for U.S. direct subsidies to the fossil fuel industry	0-100
Support for carbon tax	'strongly oppose' to 'strongly support'
How worried are you about global warming?	'not at all worried' to 'very worried'
How much do you think global warming will harm you personally? to 'strongly support'	'not at all' to 'a great deal'
When do you think global warming will start to harm people in the United States?	never' to 'They are being harmed right now'

Table 2.2: Questions used to assess support for policies aimed at mitigating climate change and to study concerns for global warming. These questions were the same for both experiments.

Sample, Survey design and procedure

We recruited a representative sample of $N = 1000$ U.S. residents on Prolific. Prolific is an online recruitment platform, which offers the option to provide researchers with a representative sample stratified across three demographics: age, sex and ethnicity. Respondents were paid \$1.1 (hourly compensation \$6.6). While our sample was representative across these dimensions, we note that Democrats were over-represented. This is an unfortunate standard feature of samples recruited online (Arechar and Rand, 2021).

At the beginning of the experiment participants saw a text containing information about the IPCC and the IPCC Report. We also informed them that the graphs they would see were based on information from the IPCC Report. After the introduction, participants were randomly assigned to one of the two groups.

Participants were then asked three sets of questions related with: (*i*) support for policies aimed at mitigating climate change (see Table 2.2); (*ii*) perception of the dangers posed by climate change (see Table 2.2) (*iii*); understanding of the graph (see Table 2.3). Respondents answered all these questions while seeing the figure to which they were initially assigned. Understanding questions force respondents to think about the figure in a very different way from which they would normally do when seeing the figure on a website. Therefore, they were included at the end to avoid anchoring the responses provided to the first two sets of questions.

Before the understanding questions participants were asked to complete an attention check question. We note that no one failed the attention check in this survey and hence all the

Question	Range
Identifying the statements that correctly describes changes of extreme events in the area WNA (Western North America)? (U1)	Five possible answers, of which one correct.
Identifying if there areas in which agricultural and ecological droughts are decreasing but heavy precipitations are increasing (U2)	Four answers, of which one correct
Hot extremes have INCREASED in the MAJORITY of the areas (U3)	True/False
Heavy precipitations have INCREASED in the MAJORITY of the areas (U4)	True/False
'Agricultural and ecological drought have INCREASED in the MAJORITY of the areas' (U5)	True/False
'There are NO AREAS in which hot extremes have DECREASED' (U6)	True/False
'There are NO AREAS in which precipitations have DECREASED' (U7)	True/False
'There are NO AREAS in which Agricultural and ecological drought have DECREASED' (U8)	True/False
'There are more areas with medium confidence in the human contribution to changes in heavy precipitations than areas with medium confidence in the human contribution to changes in agricultural and ecological droughts' (U9)	True/False

Table 2.3: Questions used to assess understanding of SPM.3. These questions were used only in Study I.

data was used for the analysis with no further restrictions other than those needed to study the heterogeneous treatment effects.

In line with the literature on graph comprehension, our questions aimed at capturing three different levels of graph understanding (Friel et al., 2001; Galesic and Garcia-Retamero, 2011). The first question level relates to the ability to read the data represented in the graph, for example by finding specific information. The second relates to the ability to identify relationship in the data as shown in SPM.3. The third relates to the ability to extrapolate information from the data, for example by making predictions. As SPM.3 does not convey information on trends over time, we focus our understanding questions on the first two dimensions of graph literacy: reading the data and identifying relationship in the data.

Increasing consistency in terms of colours within one graph might reduces consistency across graphs. Our treatment of SPM.3 has exactly this effect. Describing increases of

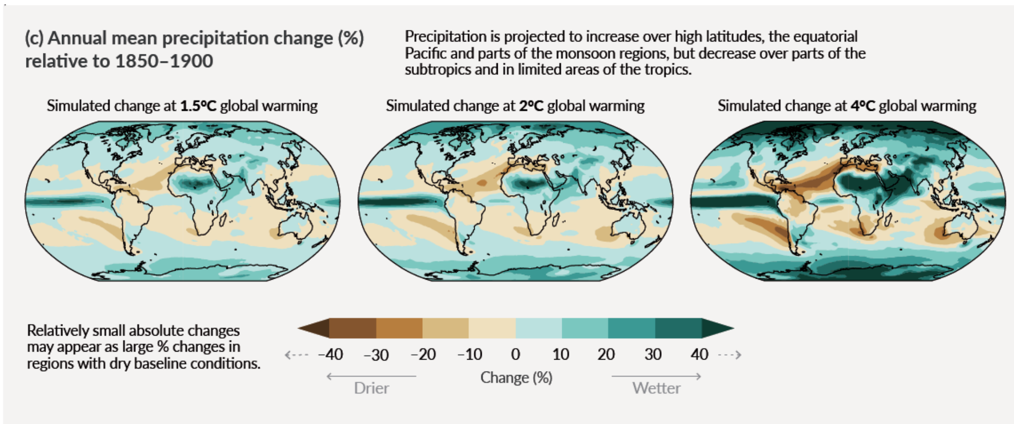

Figure 2.4: Figure SPM.5(c). It is shown to respondents with the same colours used in the IPCC Report.

extreme events in all three panels of the SPM.3 in red increases the internal consistency of the Figure. However, as other figures in the SPM do not use red to describe increases in precipitation it also reduce consistency across figures. For this reason, we further test whether our treatment influences the understanding of another figure in the SPM 5(c) (see Figure 2.4), which describes precipitation changes (see Table 2.4).

Question	Range
Identifying if there are more areas in which precipitations decrease by 30% or more in the 1.5°C or in the 4°C scenario	Four possible answers, of which one correct
Identifying if there are more areas in which precipitations increase by 30% or more in the 1.5°C or in the 4°C	Four possible answers, of which one correct

Table 2.4: Questions used to assess understanding of SPM.5(c). These questions were used only in Study I.

After having answered the questions related with our dependant variables, respondents answered a series of questions that we use as control. Control questions can be grouped in: (*i*) graph literacy, (*ii*) climate literacy, (*iii*) colour related controls, (*iv*) standard demographic questions.

2.4.3 Study II

Visual and experimental manipulation

Our experimental manipulation in study II related with the main panel of the SPM.4 Figure of the SPM of the first part of the IPCC Report, which was included by the Financial Times in one of its articles but with different colours and other minor formatting differences.

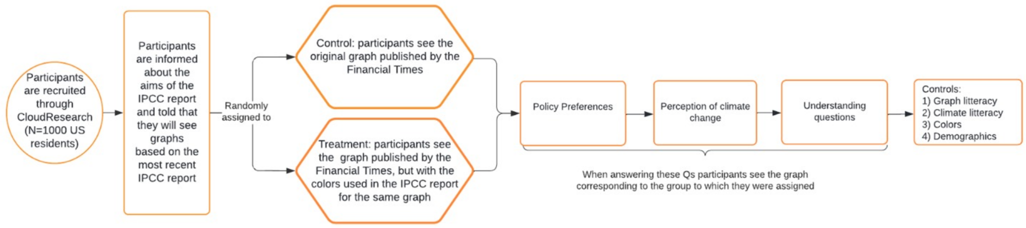

Figure 2.5: Flow of Study II

Our goal was to isolate the effect of the choice of colours made by the Financial Times. Therefore, we randomly assigned half participants to see the figure as it appeared on the Financial Times. The other half was assigned to see the same figure, but with the colours used in the IPCC Report.[2] Figure 2.5 summarizes the flow of Study II.

Sample, Survey design and procedure

We recruited a representative sample of $N = 1000$ U.S. residents on Cloudresearch. Unlike Prolific, Cloudresearch does not automatically provide a representative sample to researchers. Thus, to ensure that our sample was stratified it across the same demographics we launched the experiment several times, creating restrictions by age, gender and race to match the quotas given by Prolific for representative samples and ensure comparability. As soon as the target quotas were recruited the experiment was closed for that category. Respondents were paid $0.9 (hourly compensation $6.75). At the beginning of the experiment, all respondents saw the same message shown in study one. After the introduction, participants were randomly assigned to the two groups. Participants were then asked three sets of questions related with: (*i*) support for policies aimed at mitigating climate change (see Table 2.2); (*ii*) perception of the dangers posed by climate change (see Table 2.2) (*iii*); understanding of the graph (see Table 2.5).

The first two groups of questions were the same as in Study I (see Table 2.2). Instead, understanding questions had to be adapted to test participants' understanding of a different graph (See Table 2.5). In line with Study I, in this study the respondents answered all these questions while seeing the figure to which they were assigned.

After having answered the understanding questions, respondents answered the same control

[2]We note that the IPCC figure contained several other typographic differences, e.g., in the IPCC figure there were more ticks labelled on the axes. To isolate the impact of colours we used the Financial Times figure and changed only the colours of the curves and of the background to match the colours chosen by the IPCC.

Question	**Range**
Estimating when in the "very high" scenario $GtCO_2/yr$ will reach 100? (U1)	Five possible answers, of which one correct.
Estimating distance at various points in time between curves representing various scenarios (U2, composed by U2_medhigh, U2_lowvlow, U2_highvhigh, U2_lowhigh and a score U2_score)	Respondents must rank the possible alternatives
Formulating predictions based on the scenarios	Four possible answers, one of which correct.

Table 2.5: Questions used to assess understanding of SPM.5(c). These questions were used only in Study II.

questions as in Study I on: (*i*) graph literacy, (*ii*) climate literacy, (*iii*) colour related controls, (*iv*) standard demographic questions.

2.5 Results

2.5.1 Study I

We start by reporting the summary statistics of the first experiment (Table 2.8).

	All		Control		Treatment	
	mean	sd	mean	sd	mean	sd
Support for fossil fuel subsidy (in billions)	18.14	18.54	17.32	17.64	18.90	19.32
Support for a carbon tax	2.15	1.47	2.15	1.48	2.15	1.46
Worry about climate change	2.94	1.25	2.96	1.24	2.92	1.26
Global warming: Personal harm	1.76	0.93	1.76	0.92	1.75	0.93
Global warming: harm to US	3.89	1.61	3.93	1.57	3.85	1.64
U1 (% correct)	0.63	0.48	0.64	0.48	0.63	0.48
U2 (% correct)	0.63	0.48	0.60	0.49	0.66	0.47
U3 (% correct)	0.94	0.24	0.95	0.23	0.94	0.24
U4 (% correct)	0.49	0.50	0.49	0.50	0.50	0.50
U5 (% correct)	0.59	0.49	0.56	0.50	0.61	0.49
U6 (% correct)	0.84	0.37	0.84	0.37	0.84	0.37
U7 (% correct)	0.76	0.43	0.73	0.44	0.79	0.41
U8 (% correct)	0.87	0.34	0.87	0.33	0.86	0.34
U9 (% correct)	0.53	0.50	0.54	0.50	0.52	0.50
U_total (% correct)	6.29	2.09	6.22	2.02	6.35	2.15
Observations	977		476		501	

Table 2.6: Summary statistics (mean and sd) for the outcome variables we investigate (policy support, perception of climate change damages and understanding questions) for Study I.

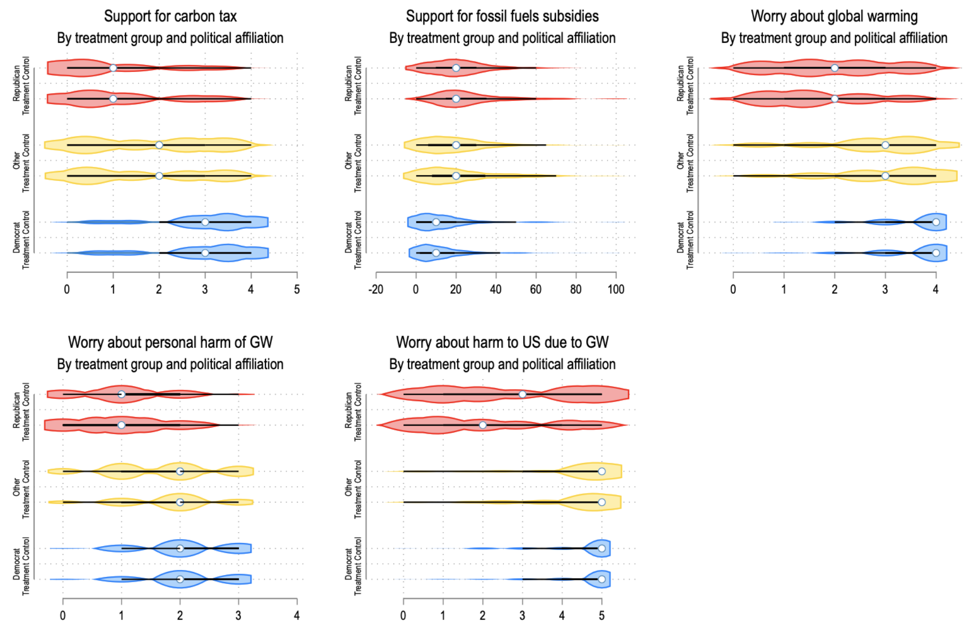

Figure 2.6: Study I: Effect of the treatment on Democrats, Republican and Others on the stated: *i*) support for carbon tax (top left); *ii*) support for fossil fuel (top centre); *iii*) worry about global warming (top right); *iv*) worry about personal harm due to global warming (bottom left); and *v*) worry about harm to the U.S. due to global warming (bottom centre).

Figure 2.6 shows the effect of our treatment given political affiliation, i.e., if the participant identifies as a Democrat, a Republican or something else (“Other").

Notwithstanding some differences in the summary statistics for our dependent variables, we do not find significant results with respect to the full sample, Democrats and Others. However, we observe that the treatment has a significant impact on Republicans (see Table 2.7). In particular, we observe that the treatment increases Republicans’ understanding of the figure ($p < 0.001$), while also increasing their support for a carbon tax ($p = 0.026$). Full regression tables are included in the Appendix.

With respect to consistency in the colour scales across graphs, we observe no significant differences between the performance of the groups in terms of understanding of the second graph (see Table 2.4).

2.5.2 Study II

Table 2.8 reports the summary statistics of the second experiment.

We find that the choice of the Financial Times of using colours with a lower semantic discriminability had virtually no effect on any of our dependent variables (see Table 2.8).

	(1) Support for subsidies to fossil fuels (in billions)	(2) Support for a carbon tax	(3) U_tot
treatment	4.474	0.803**	0.970***
	(0.118)	(0.026)	(0.002)
Observations	176	182	182
(Pseudo)R^2	0.236	0.118	0.091

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.7: OLS beta coefficients (Column 1) and Ordered Logit Coefficients (Columns 2-3) deriving from regressions with the participant's desired subsidies for fossil fuels (Column 1), support for a carbon tax (Column 2) and overall understanding (Column 3) as the dependent variable and a binary variable to measure the impact of being in the treatment group with respect to the control group. The regressions are ran controlling for demographics, graph literacy, climate literacy and the perceived levels of arousal and pleasure of the participants elicited by the palette with the colours of the figure participants see. Each regression is ran restricting the sample to include only participants who identify as "Republican" and political affiliation is removed from the set of demographic controls.

	(1) All		(2) FT Pink		(3) White	
	mean	sd	mean	sd	mean	sd
Support for fossil fuel subsidy (in billions)	22.07	20.73	21.38	20.25	22.77	21.20
Support for a carbon tax	1.96	1.45	1.95	1.46	1.98	1.44
Worry about climate change	2.79	1.31	2.85	1.31	2.74	1.32
Global warming: Personal harm	1.67	0.95	1.70	0.94	1.65	0.97
Global warming: harm to US	3.64	1.79	3.71	1.76	3.56	1.82
U1 (% correct)	0.79	0.41	0.79	0.41	0.80	0.40
U2_medhigh (% correct)	0.27	0.44	0.27	0.44	0.27	0.44
U2_lowvlow (% correct)	0.23	0.42	0.22	0.41	0.25	0.43
U2_highvhigh (% correct)	0.36	0.48	0.36	0.48	0.36	0.48
U2_lowhigh (% correct)	0.38	0.49	0.38	0.49	0.39	0.49
U2_score (% correct)	1.24	1.41	1.23	1.40	1.26	1.43
U3 (% correct)	0.40	0.49	0.40	0.49	0.41	0.49
Observations	1148		574		570	

Table 2.8: Summary statistics (mean and sd) for the dependent variables we investigate (policy support, perception of climate change damages and understanding questions) for Experiment II

We note that this is not because the treatment effect is a precisely estimated zero, but rather because the impact of the treatment is noisy.

	(1) U1_right	(2) U2_score	(3) U3_right	(4) U_tot
treatment	0.125	0.0397	-0.0802	0.0502
	(0.577)	(0.753)	(0.568)	(0.685)
Observations	928	930	930	930
Pseudo R^2	0.179	0.036	0.060	0.032
chi2	109.1	.	72.26	122.6

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.9: Logit Coefficients (Columns 1 and 3) and Ordered Logit Coefficients (Column 2) deriving from regressions with perceptions as the dependent variable and a binary variable to measure the impact of being in the treatment group with respect to the control group. The regressions are ran controlling for demographics, graph literacy, climate literacy and the perceived levels of arousal and pleasure of the participants elicited by the color palette of the figure participants see.

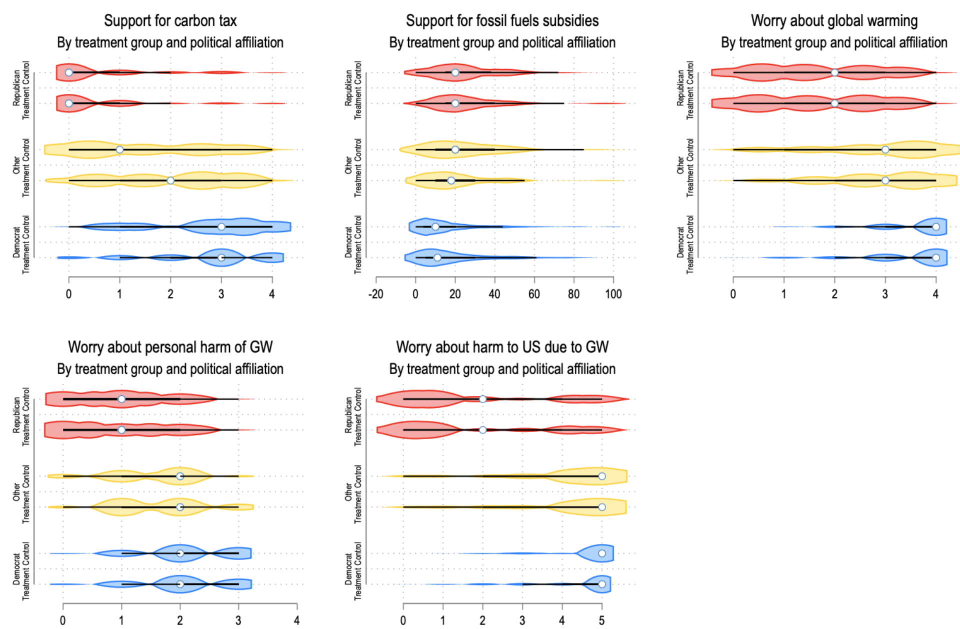

Figure 2.7: Study II: Effect of the treatment on Democrats, Republican and Others on the stated: *i*) support for carbon tax (top left); *ii*) support for fossil fuel (top centre); *iii*) worry about global warming (top right); *iv*) worry about personal harm due to global warming (bottom left); and *v*) worry about harm to the U.S. due to global warming (bottom centre).

Contrarily to what hypothesised by the literature (Terrado et al., 2022), we observe no difference in the understanding of the figure between the two groups, even if the colours used by the FT have a much lower semantic discriminability (see Table 2.9). We observe no consistent result even when studying the effect of the treatment on Democrats, Others and Republicans.

2.6 Discussion

Before discussing the results a preliminary caveat is in order. Visuals are formed by many components which are likely to interact with each other in ways that existing evidence does not allow one to predict. For instance, a bright red colour might have a different effect depending on the kind of graph in which it is used and on whether there are textual explanations accompanying the graph. For this reason, we do not argue that our findings (or lack thereof) would be replicated regardless of the specific features to which the proposed treatments are applied. However, we believe that our findings can still provide useful guidance.

To begin with, passing the regulations needed to tackle climate change without the support of Republicans is extremely problematic. However, persuading Republicans that actions are needed has proven complex and assertive language or persuasive messages have been shown to trigger reactance (Ma et al., 2019). For this reason, in our first experiment we have investigated if an appropriate choice of colours in climate visuals can affect Republicans' perception of policies aimed at mitigating climate change. On the one hand, colours are known to influence preferences and behaviours. On the other, the choice of colours in a visual is unlikely to make people feel pressured into changing their views and therefore is unlikely to trigger reactance.

Our results highlight that colours *can* indeed affect Republicans' stated support of a policy as controversial as a carbon tax ($p = 0.026$). We emphasise, in line with the initial disclaimer, that our results do not allow us to say that colours will always affect Republican's preferences. However, our results do prove that colours have the potential to do so. The effect of colours on Republican's preferences could depend on three possible mechanisms (*i*): the higher semantic discriminability of the colours used in the treatment might have improved Republicans' understanding of the climate crisis, which in turn could have led them to state that they support more a carbon tax; (*ii*) the more extensive use in the treatment of colours generally associated with bad scenarios like red, might have made Republicans more concerned about climate change,which in turn could have led them to state that they support more a carbon tax; (*iii*) the use of a consistent scale have facilitated

Republicans' understanding of the graph without making them feel coerced to change opinion, which in turn could have lead them to that they support more a carbon tax. We have reasons to believe that the third channel is the most likely.

To begin with, in the second experiment we observe that using colours with higher semantic discriminability did not improve understanding, and therefore this might not be the key driver behind our results (first mechanism). Moreover, we do not observe that Republicans become more concerned about the climate crisis, and hence the result cannot be driven by the emotional impact of a more massive use of a colour like red that in many countries is associated with danger and negative outcomes (second mechanism). Thus, we hypothesise that the third mechanism is at play. A consistent colour scale has improved understanding ($p < 0.001$), and increased their stated support for a carbon tax ($p = 0.026$). From this perspective, it would become important to identify other channels that could improve Republicans' understanding of the climate crisis, without triggering the perception that the information conveyed is part of the cultural war surrounding climate change in U.S. Moreover, it is important to carry out other studies to better understand the role played by colours in influencing people's reaction to climate visuals, and under which conditions colour can foster support for policies aimed at mitigating climate change.

Another interesting result is that colours did not have an impact on any of our dependent variables in our second experiment. The literature has hypothesised that using colours with lower semantic discriminability can hinder understanding of climate visuals (Terrado et al., 2022), thus it was reasonable to expect a difference between the two groups at least in terms of understanding. In fact, the colours used by the graph included in the IPCC Report had high semantic discriminability, whereas the colours used by the FT had low semantic discriminability. Given that we draw inference from a large representative sample, we believe that this finding calls for further research. We clearly do not rule out that in many contexts the choice of colours with low semantic discriminability might hinder understanding. However, the literature seems to have hypothesised a monotonic relationship in which an increase in discriminability always resulted in an increase in understanding. Our result suggests that the relationship might be more nuanced.

Last, we found that reducing consistency in the choice of colours among graphs did not worsen understanding. Clearly, this does not suggest that consistency among graphs is never relevant. However, our finding suggests that it is important to study when consistency within a graph should be prioritised over consistency across graphs, as the latter might not always be as important. There are at least two instances in which consistency within graph should be prioritised. First, when one believes that people might not be interested in reading the entire report, and instead will focus on single paragraphs to find some specific information. This is likely to be the case for reports that are particularly long and cover diverse topics. Second, when one believes that people are likely to learn the information not from the report directly, but from newspapers. As newspapers will generally only include one or a few figures from the report, in this context maximising consistency within each figure might be more relevant.

2.7 Conclusion

We carried out two studies to investigate the role that colours play in the context of climate visualisation. In our first study, we observed that using consistent colour scales improved Republican respondents' understanding of the climate visual. Moreover, Republican respondents who saw a consistent colour scale were also more likely to support a carbon tax. This suggests that improving the understanding of climate change can, at least in some instances, increase the level of support for policies aimed at mitigating its impacts. In our second study, we had hypothesised that using colours with a low discriminability would worsen understanding of the climate visual. However, contrarily to the prediction of the literature, our results show that ignoring standard symbolism in the choice of colours does not lower comprehension. We also do not find evidence that the choice of colours affects the emotional response to climate-related information. Future research is needed to establish whether different characteristics of colours in visuals (e.g., the level of contrast used in an image) affect how people respond to it.

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2.A Appendix

2.A.1 Study I

Table 2.A.1: Summary statistics for key demographics of the two samples (treatment and control) for Study I. The samples for this experiment were recruited on Prolific and are representative samples of the U.S. population.

	Group								
	Control			Treatment			Total		
	No.	%	%	No.	%	%	No.	%	%
Gender									
Other/Prefer not to declare	21	4.4	4.4	13	2.6	2.6	34	3.5	3.5
Female	231	48.3	52.7	246	49.0	51.6	477	48.7	52.1
Male	226	47.3	100.0	243	48.4	100.0	469	47.9	100.0
Total	478	100.0		502	100.0		980	100.0	
Age									
18-25 years old	70	14.6	14.6	85	16.9	16.9	155	15.8	15.8
26-35 years old	85	17.8	32.4	110	21.9	38.8	195	19.9	35.7
36-45 years old	72	15.1	47.5	90	17.9	56.8	162	16.5	52.2
46-55 years old	107	22.4	69.9	68	13.5	70.3	175	17.9	70.1
56-65 years old	91	19.0	88.9	83	16.5	86.9	174	17.8	87.9
66-75 years old	46	9.6	98.5	54	10.8	97.6	100	10.2	98.1
>75 years old	7	1.5	100.0	12	2.4	100.0	19	1.9	100.0
Total	478	100.0		502	100.0		980	100.0	
Income									
$10,000 to $19,999	41	8.6	8.6	39	7.8	7.8	80	8.2	8.2
$100,000 to $149,999	73	15.3	23.9	57	11.4	19.2	130	13.3	21.5
$150,000 or more	41	8.6	32.5	33	6.6	25.7	74	7.6	29.0
$20,000 to $29,999	56	11.7	44.2	52	10.4	36.1	108	11.0	40.1
$30,000 to $39,999	42	8.8	53.0	65	13.0	49.1	107	10.9	51.0
$40,000 to $49,999	45	9.4	62.5	48	9.6	58.7	93	9.5	60.5
$50,000 to $59,999	31	6.5	69.0	44	8.8	67.5	75	7.7	68.2
$60,000 to $69,999	46	9.6	78.6	33	6.6	74.1	79	8.1	76.3
$70,000 to $79,999	23	4.8	83.4	34	6.8	80.8	57	5.8	82.1
$80,000 to $89,999	33	6.9	90.4	30	6.0	86.8	63	6.4	88.5
$90,000 to $99,999	22	4.6	95.0	33	6.6	93.4	55	5.6	94.2
Less than $10,000	24	5.0	100.0	33	6.6	100.0	57	5.8	100.0
Total	477	100.0		501	100.0		978	100.0	
Education									
Associate degree in college (2-year)	49	10.3	10.3	48	9.6	9.6	97	9.9	9.9
Bachelor's degree in college (4-year)	174	36.5	46.8	214	42.6	52.2	388	39.6	49.5
Doctoral degree	3	0.6	47.4	10	2.0	54.2	13	1.3	50.9
High school graduate (high school diploma or equivalent including GED)	65	13.6	61.0	53	10.6	64.7	118	12.1	62.9
Less than high school degree	3	0.6	61.6	4	0.8	65.5	7	0.7	63.6
Master's degree	72	15.1	76.7	68	13.5	79.1	140	14.3	77.9
Professional degree (JD, MD)	12	2.5	79.2	7	1.4	80.5	19	1.9	79.9
Some college but no degree	99	20.8	100.0	98	19.5	100.0	197	20.1	100.0
Total	477	100.0		502	100.0		979	100.0	
Political Orientation									
Republican	95	19.9	19.9	97	19.3	19.3	192	19.6	19.6
Democrat	254	53.1	73.0	252	50.2	69.5	506	51.6	71.2
No strong preference	129	27.0	100.0	153	30.5	100.0	282	28.8	100.0
Total	478	100.0		502	100.0		980	100.0	
In full or part time employment									
	285	59.6	100.0	322	64.1	100.0	607	61.9	100.0
Total	478	100.0		502	100.0		980	100.0	
Student									
	28	5.9	100.0	29	5.8	100.0	57	5.8	100.0
Total	478	100.0		502	100.0		980	100.0	
White									
	355	74.3	100.0	368	73.3	100.0	723	73.8	100.0
Total	478	100.0		502	100.0		980	100.0	

Table 2.A.2: Preferred subsidy

	(1) Subsidy	(2) Subsidy	(3) Subsidy	(4) Subsidy	(5) Subsidy
treatment	1.622	1.467	1.710	1.439	1.629
	(0.176)	(0.224)	(0.132)	(0.199)	(0.146)
Age		-0.0810**	-0.119***	-0.123***	-0.128***
		(0.040)	(0.001)	(0.001)	(0.001)
$10,000 to $19,999		-5.313	-6.065*	-4.571	-5.749
		(0.141)	(0.099)	(0.190)	(0.105)
$20,000 to $29,999		-0.653	-1.162	-0.491	-0.906
		(0.856)	(0.744)	(0.884)	(0.793)
$30,000 to $39,999		-2.818	-2.251	-1.422	-1.934
		(0.412)	(0.514)	(0.658)	(0.563)
$40,000 to $49,999		-4.824	-3.460	-2.571	-3.464
		(0.154)	(0.330)	(0.437)	(0.304)
$50,000 to $59,999		-1.922	-4.648	-3.598	-4.443
		(0.636)	(0.233)	(0.332)	(0.233)
$60,000 to $69,999		-2.848	-1.460	-0.573	-2.161
		(0.443)	(0.701)	(0.873)	(0.532)
$70,000 to $79,999		-0.896	-2.706	-1.407	-1.944
		(0.819)	(0.484)	(0.700)	(0.604)
$80,000 to $89,999		-3.698	-4.078	-3.548	-3.941
		(0.316)	(0.281)	(0.317)	(0.284)
$90,000 to $99,999		-2.031	-2.658	-1.848	-2.446
		(0.604)	(0.483)	(0.608)	(0.514)
$100,000 to $149,999		-2.270	-2.623	-2.465	-3.235
		(0.521)	(0.465)	(0.463)	(0.352)
$150,000 or more		-1.661	-1.587	-1.285	-2.989
		(0.675)	(0.690)	(0.736)	(0.458)
High school graduate		-4.418	-6.456	-6.645	-7.227
		(0.469)	(0.231)	(0.209)	(0.166)
Some college but no degree		-7.447	-7.603	-6.513	-6.296
		(0.211)	(0.138)	(0.195)	(0.207)
Associate degree in college (2-year)		-6.115	-7.527	-6.555	-6.040
		(0.312)	(0.154)	(0.208)	(0.242)
Bachelor's degree in college (4-year)		-7.632	-7.301	-6.832	-6.169
		(0.198)	(0.156)	(0.174)	(0.218)
Master's degree		-9.023	-8.489	-8.109	-6.999
		(0.134)	(0.106)	(0.115)	(0.172)
Professional degree (JD, MD)		-14.48**	-11.04*	-10.13*	-9.130*
		(0.023)	(0.059)	(0.066)	(0.095)
Doctoral degree		-4.033	-8.669	-8.764	-8.090
		(0.653)	(0.238)	(0.206)	(0.244)
Female		2.996**	5.133***	5.139***	4.849***
		(0.015)	(0.000)	(0.000)	(0.000)
Student		-0.752	0.785	-0.567	0.0875
		(0.790)	(0.777)	(0.841)	(0.975)
Worry about climate change			-3.303***	-1.663**	-2.151***
			(0.000)	(0.027)	(0.004)
Global warming: hurting myself			0.374	-0.0746	0.0466
			(0.717)	(0.941)	(0.964)
Global warming: when does it hurt the US?			-1.040	-0.665	-0.329
			(0.102)	(0.300)	(0.609)
U1_right			-3.351**	-2.756*	-2.188
			(0.020)	(0.058)	(0.140)
U2_right			-3.897***	-3.421***	-3.318**
			(0.002)	(0.008)	(0.011)
U3_right			-6.472*	-6.173*	-6.007
			(0.080)	(0.096)	(0.106)
U4_right			1.879	1.956	2.498*
			(0.141)	(0.122)	(0.058)
U5_right			-0.299	-0.357	-0.227
			(0.824)	(0.791)	(0.863)
U6_right			-6.877***	-6.150***	-5.802***
			(0.001)	(0.002)	(0.004)
U7_right			1.124	1.144	1.178
			(0.503)	(0.486)	(0.473)
U8_right			-0.306	-0.463	-0.540
			(0.880)	(0.818)	(0.790)
U9_right			-1.556	-1.272	-0.691
			(0.209)	(0.285)	(0.564)
White				-3.007**	-2.706*
				(0.035)	(0.056)
Political Scale				1.565***	1.503***
				(0.000)	(0.001)
In full or part time employment				-0.171	-0.167
				(0.891)	(0.893)
Republican				-2.869	-3.341
				(0.199)	(0.140)
Democrat				-2.694*	-2.887*
				(0.092)	(0.076)
religion_importance				0.924*	0.511
				(0.097)	(0.355)
q1_graph_right					-0.609
					(0.776)
q2_graph_right					-1.175
					(0.371)
q3_graph_right					0.921
					(0.408)
climate_U1right					-4.623
					(0.105)
right_GHGs					-0.442
					(0.548)
climate_U3right					-0.386
					(0.736)
climate_U4right					-0.380
					(0.759)
climate_U5right					-2.071*
					(0.070)
arousal					0.00878
					(0.744)
pleasure					0.0467
					(0.121)
Constant	17.25***	29.21***	58.98***	49.86***	53.00***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	943	936	893	884	868
Adjusted R^2	0.0019	0.0312	0.1947	0.24	0.2578

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A.3: Support for tax

	(1) Tax Support	(2) Tax Support	(3) Tax Support	(4) Tax Support	(5) Tax Support
Tax Support					
treatment	0.00218	0.0125	0.0644	0.113	0.0978
	(0.985)	(0.918)	(0.620)	(0.393)	(0.470)
Age		-0.00146	0.00529	0.00805*	0.00963**
		(0.727)	(0.223)	(0.085)	(0.047)
\$10,000 to \$19,999		0.0855	-0.0305	-0.141	-0.0946
		(0.776)	(0.931)	(0.699)	(0.804)
\$20,000 to \$29,999		-0.477*	-0.249	-0.219	-0.305
		(0.095)	(0.460)	(0.529)	(0.392)
\$30,000 to \$39,999		0.0493	0.124	0.165	0.183
		(0.858)	(0.701)	(0.620)	(0.597)
\$40,000 to \$49,999		0.263	0.429	0.523	0.579
		(0.356)	(0.212)	(0.144)	(0.117)
\$50,000 to \$59,999		0.181	0.503	0.517	0.405
		(0.570)	(0.158)	(0.170)	(0.285)
\$60,000 to \$69,999		-0.242	-0.207	-0.262	-0.277
		(0.430)	(0.570)	(0.484)	(0.472)
\$70,000 to \$79,999		-0.363	-0.227	-0.146	-0.185
		(0.262)	(0.559)	(0.717)	(0.657)
\$80,000 to \$89,999		-0.181	0.145	0.247	0.176
		(0.579)	(0.682)	(0.498)	(0.641)
\$90,000 to \$99,999		-0.142	-0.0802	0.0634	0.105
		(0.668)	(0.832)	(0.875)	(0.797)
\$100,000 to \$149,999		-0.129	0.260	0.396	0.443
		(0.664)	(0.429)	(0.238)	(0.197)
\$150,000 or more		0.180	0.568	0.692*	0.762*
		(0.578)	(0.116)	(0.069)	(0.051)
High school graduate		0.525	1.639**	1.802**	1.700**
		(0.124)	(0.048)	(0.018)	(0.015)
Some college but no degree		0.882***	1.674**	1.732**	1.593**
		(0.009)	(0.041)	(0.022)	(0.022)
Associate degree in college (2-year)		0.641*	1.461*	1.452*	1.278*
		(0.070)	(0.082)	(0.061)	(0.075)
Bachelor's degree in college (4-year)		0.768**	1.455*	1.514**	1.351**
		(0.019)	(0.073)	(0.043)	(0.049)
Master's degree		0.802**	1.343	1.396*	1.166*
		(0.031)	(0.103)	(0.068)	(0.096)
Professional degree (JD, MD)		1.681***	2.067**	2.079**	2.029***
		(0.000)	(0.018)	(0.011)	(0.008)
Doctoral degree		0.0276	1.020	1.047	0.676
		(0.965)	(0.297)	(0.288)	(0.470)
Female		-0.0344	-0.412***	-0.486***	-0.442***
		(0.774)	(0.001)	(0.000)	(0.002)
Student		0.251	-0.0868	0.00667	0.0164
		(0.256)	(0.741)	(0.981)	(0.955)
Worry about climate change			0.822***	0.632***	0.657***
			(0.000)	(0.000)	(0.000)
Global warming: hurting myself			0.181	0.237**	0.239**
			(0.113)	(0.039)	(0.044)
Global warming: when does it hurt the US?			0.289***	0.234***	0.213***
			(0.000)	(0.001)	(0.003)
U1_right			0.149	0.0551	-0.00486
			(0.320)	(0.717)	(0.975)
U2_right			0.355**	0.264*	0.196
			(0.018)	(0.082)	(0.206)
U3_right			-0.0980	-0.0944	-0.0915
			(0.761)	(0.775)	(0.783)
U4_right			0.00717	-0.0278	-0.0413
			(0.957)	(0.840)	(0.770)
U5_right			-0.228	-0.241	-0.194
			(0.125)	(0.119)	(0.218)
U6_right			-0.0298	-0.0558	-0.0902
			(0.890)	(0.808)	(0.705)
U7_right			-0.0966	-0.118	-0.100
			(0.621)	(0.570)	(0.632)
U8_right			-0.0534	-0.0963	-0.0848
			(0.796)	(0.656)	(0.700)
U9_right			0.269*	0.293**	0.273*
			(0.062)	(0.048)	(0.074)
White				0.129	0.101
				(0.430)	(0.546)
Political Scale				-0.219***	-0.220***
				(0.000)	(0.000)
In full or part time employment				-0.0362	-0.0269
				(0.815)	(0.866)
Republican				0.216	0.276
				(0.357)	(0.248)
Democrat				0.249	0.285
				(0.187)	(0.137)
religion_importance				-0.121*	-0.101
				(0.058)	(0.123)
q1_graph_right					0.197
					(0.494)
q2_graph_right					0.327**
					(0.031)
q3_graph_right					-0.0202
					(0.886)
climate_U1right					0.0847
					(0.738)
right_GHGs					-0.0437
					(0.586)
climate_U3right					-0.366***
					(0.007)
climate_U4right					0.235
					(0.109)
climate_U5right					0.0843
					(0.564)
arousal					0.00171
					(0.616)
pleasure					0.00237
					(0.514)
Observations	959	952	907	898	882
Pseudo R^2	0.000	0.010	0.161	0.182	0.188
chi2	0.000357	40.91	378.4	448.0	451.8

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A.4: Worry about global warming

	(1)	(2)	(3)	(4)	(5)
	Worry about climate change	Worry about climate change	Worry about climate change	Worry about climate change	Worry about climate change
Worry about climate change					
treatment	-0.0648	-0.0107	-0.0510	0.0429	0.0349
	(0.605)	(0.929)	(0.688)	(0.753)	(0.805)
Age	-0.00309		-0.00364	-0.000213	0.000718
	(0.480)		(0.409)	(0.964)	(0.884)
\$10,000 to \$19,999	0.245		0.245	-0.0610	-0.0968
	(0.493)		(0.506)	(0.871)	(0.800)
\$20,000 to \$29,999	-0.138		-0.138	-0.116	-0.0662
	(0.656)		(0.668)	(0.718)	(0.845)
\$30,000 to \$39,999	0.0862		0.0450	0.00296	-0.0703
	(0.759)		(0.878)	(0.992)	(0.833)
\$40,000 to \$49,999	0.0542		0.00758	-0.0593	-0.0189
	(0.860)		(0.981)	(0.860)	(0.957)
\$50,000 to \$59,999	-0.109		-0.109	-0.172	-0.166
	(0.740)		(0.748)	(0.631)	(0.657)
\$60,000 to \$69,999	0.00219		-0.0450	-0.0560	-0.0934
	(0.994)		(0.878)	(0.868)	(0.793)
\$70,000 to \$79,999	-0.124		-0.120	-0.127	-0.161
	(0.727)		(0.744)	(0.742)	(0.688)
\$80,000 to \$89,999	-0.360		-0.322	-0.104	-0.0841
	(0.243)		(0.311)	(0.759)	(0.815)
\$90,000 to \$99,999	-0.102		-0.0814	0.113	0.0950
	(0.790)		(0.839)	(0.793)	(0.837)
\$100,000 to \$149,999	-0.371		-0.401	-0.0833	-0.174
	(0.214)		(0.201)	(0.798)	(0.618)
\$150,000 or more	-0.357		-0.407	0.00563	0.0160
	(0.271)		(0.224)	(0.988)	(0.967)
High school graduate	-1.081		-1.078	-0.226	-0.173
	(0.403)		(0.413)	(0.840)	(0.885)
Some college but no degree	-0.663		-0.639	-0.226	-0.203
	(0.607)		(0.626)	(0.839)	(0.863)
Associate degree in college (2-year)	-0.804		-0.719	-0.179	-0.176
	(0.533)		(0.584)	(0.873)	(0.882)
Bachelor's degree in college (4-year)	-0.560		-0.509	-0.0103	0.0692
	(0.662)		(0.696)	(0.993)	(0.953)
Master's degree	-0.525		-0.470	-0.0435	0.0236
	(0.683)		(0.720)	(0.969)	(0.984)
Professional degree (JD, MD)	0.0986		0.154	0.456	0.532
	(0.941)		(0.910)	(0.703)	(0.676)
Doctoral degree	-0.957		-0.887	-0.369	-0.530
	(0.504)		(0.547)	(0.757)	(0.678)
Female	0.433^{***}		0.391^{***}	0.250^{*}	0.271^{*}
	(0.000)		(0.002)	(0.071)	(0.063)
Student	0.436		0.453	0.686^{**}	0.699^{**}
	(0.123)		(0.126)	(0.034)	(0.033)
U1_right		-0.0186	0.00706	-0.238	-0.205
		(0.894)	(0.961)	(0.133)	(0.226)
U2_right		-0.0979	-0.102	-0.211	-0.230
		(0.477)	(0.470)	(0.175)	(0.152)
U3_right		0.733^{**}	0.728^{**}	0.571^{*}	0.543
		(0.010)	(0.011)	(0.076)	(0.113)
U4_right		-0.174	-0.175	-0.189	-0.142
		(0.172)	(0.187)	(0.188)	(0.344)
U5_right		-0.149	-0.154	-0.256	-0.249
		(0.300)	(0.305)	(0.113)	(0.144)
U6_right		-0.0630	-0.00278	-0.0948	-0.0684
		(0.760)	(0.990)	(0.698)	(0.789)
U7_right		0.233	0.188	0.155	0.172
		(0.210)	(0.320)	(0.437)	(0.395)
U8_right		0.0362	0.0575	0.123	0.0786
		(0.864)	(0.786)	(0.617)	(0.757)
U9_right		-0.0174	-0.0251	-0.0396	-0.0725
		(0.893)	(0.851)	(0.791)	(0.638)
White				0.393^{**}	0.384^{**}
				(0.018)	(0.025)
Political Scale				-0.459^{***}	-0.449^{***}
				(0.000)	(0.000)
In full or part time employment				-0.0551	-0.105
				(0.732)	(0.527)
Republican				-0.357	-0.386^{*}
				(0.112)	(0.089)
Democrat				0.814^{***}	0.845^{***}
				(0.000)	(0.000)
religion_importance				0.103	0.0847
				(0.109)	(0.191)
q1_graph_right					-0.0903
					(0.764)
q2_graph_right					0.00282
					(0.986)
q3_graph_right					0.0214
					(0.885)
climate_U1right					0.145
					(0.590)
right_GHGs					-0.0689
					(0.461)
climate_U3right					0.181
					(0.210)
climate_U4right					0.0315
					(0.843)
climate_U5right					0.466^{***}
					(0.002)
arousal					0.00678^{**}
					(0.049)
pleasure					-0.000261
					(0.944)
Observations	949	956	949	940	922
Pseudo R^2	0.013	0.006	0.018	0.153	0.165
chi2	34.45	13.51	47.41	348.4	372.5

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A.5: Perceived harm from global warming

	(1) GW hurts me	(2) GW hurts me	(3) GW hurts me	(4) GW hurts me	(5) GW hurts me
GW hurts me					
treatment	-0.0748	0.00384	-0.0752	0.00344	-0.0283
	(0.555)	(0.975)	(0.558)	(0.979)	(0.833)
Age	-0.0172***		-0.0180***	-0.0162***	-0.0157***
	(0.000)		(0.000)	(0.001)	(0.001)
\$10,000 to \$19,999	-0.0178		-0.00847	-0.195	-0.276
	(0.962)		(0.983)	(0.619)	(0.497)
\$20,000 to \$29,999	-0.616*		-0.631*	-0.473	-0.437
	(0.066)		(0.070)	(0.169)	(0.230)
\$30,000 to \$39,999	-0.302		-0.344	-0.324	-0.446
	(0.345)		(0.305)	(0.341)	(0.216)
\$40,000 to \$49,999	-0.651**		-0.679**	-0.709**	-0.731**
	(0.042)		(0.042)	(0.040)	(0.043)
\$50,000 to \$59,999	-0.626		-0.648	-0.583	-0.607
	(0.112)		(0.108)	(0.158)	(0.143)
\$60,000 to \$69,999	-0.429		-0.513	-0.459	-0.512
	(0.200)		(0.140)	(0.202)	(0.172)
\$70,000 to \$79,999	-0.773**		-0.801**	-0.714*	-0.769**
	(0.028)		(0.028)	(0.054)	(0.042)
\$80,000 to \$89,999	-0.923**		-0.933**	-0.702*	-0.821**
	(0.010)		(0.011)	(0.058)	(0.039)
\$90,000 to \$99,999	-0.652*		-0.645*	-0.419	-0.493
	(0.083)		(0.097)	(0.310)	(0.253)
\$100,000 to \$149,999	-1.048***		-1.060***	-0.832**	-0.983***
	(0.001)		(0.002)	(0.018)	(0.008)
\$150,000 or more	-0.671*		-0.739**	-0.310	-0.398
	(0.055)		(0.039)	(0.393)	(0.292)
High school graduate	-0.727		-0.694	-0.0263	-0.0980
	(0.523)		(0.521)	(0.981)	(0.931)
Some college but no degree	-0.292		-0.249	0.113	0.0199
	(0.797)		(0.817)	(0.917)	(0.986)
Associate degree in college (2-year)	0.0655		0.151	0.744	0.675
	(0.954)		(0.889)	(0.496)	(0.550)
Bachelor's degree in college (4-year)	-0.0844		-0.0134	0.477	0.447
	(0.940)		(0.990)	(0.659)	(0.690)
Master's degree	0.00497		0.0778	0.482	0.426
	(0.997)		(0.942)	(0.658)	(0.705)
Professional degree (JD, MD)	0.409		0.537	0.692	0.642
	(0.730)		(0.633)	(0.546)	(0.588)
Doctoral degree	-0.714		-0.649	-0.413	-0.797
	(0.597)		(0.619)	(0.734)	(0.527)
Female	0.538***		0.491***	0.432***	0.484***
	(0.000)		(0.000)	(0.002)	(0.001)
Student	0.426		0.420	0.365	0.348
	(0.126)		(0.138)	(0.243)	(0.278)
U1_right		-0.196	-0.176	-0.341**	-0.281*
		(0.172)	(0.249)	(0.027)	(0.076)
U2_right		-0.0793	-0.137	-0.150	-0.138
		(0.577)	(0.357)	(0.317)	(0.373)
U3_right		0.393	0.395	0.291	0.201
		(0.214)	(0.208)	(0.373)	(0.559)
U4_right		-0.294**	-0.229*	-0.235*	-0.198
		(0.022)	(0.083)	(0.082)	(0.158)
U5_right		0.0683	0.0133	-0.0551	-0.0964
		(0.615)	(0.926)	(0.704)	(0.520)
U6_right		-0.0338	0.0985	0.0335	-0.0252
		(0.871)	(0.640)	(0.884)	(0.918)
U7_right		0.180	0.132	0.0623	0.103
		(0.310)	(0.467)	(0.743)	(0.603)
U8_right		0.0439	0.147	0.223	0.222
		(0.838)	(0.519)	(0.358)	(0.370)
U9_right		-0.0376	-0.0241	-0.00831	-0.00529
		(0.770)	(0.858)	(0.953)	(0.971)
White				-0.0763	-0.0582
				(0.636)	(0.724)
Political Scale				-0.347***	-0.341***
				(0.000)	(0.000)
In full or part time employment				-0.198	-0.289*
				(0.191)	(0.072)
Republican				-0.570**	-0.635***
				(0.014)	(0.007)
Democrat				0.294	0.242
				(0.127)	(0.228)
religion_importance				0.148**	0.137**
				(0.013)	(0.028)
q1_graph_right					0.0730
					(0.782)
q2_graph_right					-0.00310
					(0.983)
q3_graph_right					0.255*
					(0.074)
climate_U1right					0.131
					(0.672)
right_GHGs					-0.0114
					(0.899)
climate_U3right					0.198
					(0.149)
climate_U4right					0.220
					(0.144)
climate_U5right					0.530***
					(0.000)
arousal					0.00727**
					(0.033)
pleasure					0.000111
					(0.975)
Observations	909	916	909	900	884
Pseudo R^2	0.030	0.005	0.034	0.117	0.132
chi2	66.04	11.35	78.09	255.4	267.9

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A.6: Speed at which global warming hurts the US

	(1)	(2)	(3)	(4)	(5)
	GW hurts USA	GW hurts USA	GW hurts USA	GW hurts USA	GW hurts USA
GW hurts USA					
treatment	-0.109	-0.0873	-0.107	-0.0658	-0.0602
	(0.403)	(0.492)	(0.420)	(0.646)	(0.682)
Age	0.000406		-0.000589	0.00503	0.00370
	(0.927)		(0.896)	(0.306)	(0.486)
\$10,000 to \$19,999	-0.278		-0.241	-0.349	-0.430
	(0.447)		(0.510)	(0.387)	(0.316)
\$20,000 to \$29,999	-0.533		-0.529	-0.312	-0.393
	(0.108)		(0.108)	(0.428)	(0.345)
\$30,000 to \$39,999	-0.275		-0.353	-0.294	-0.416
	(0.394)		(0.269)	(0.431)	(0.299)
\$40,000 to \$49,999	-0.346		-0.415	-0.358	-0.313
	(0.307)		(0.215)	(0.355)	(0.454)
\$50,000 to \$59,999	-0.521		-0.499	-0.411	-0.449
	(0.157)		(0.170)	(0.325)	(0.308)
\$60,000 to \$69,999	-0.725**		-0.771**	-0.804**	-0.885**
	(0.029)		(0.021)	(0.049)	(0.042)
\$70,000 to \$79,999	-0.522		-0.513	-0.344	-0.394
	(0.179)		(0.178)	(0.414)	(0.366)
\$80,000 to \$89,999	-0.482		-0.450	-0.0153	-0.203
	(0.189)		(0.223)	(0.971)	(0.655)
\$90,000 to \$99,999	-0.643*		-0.668*	-0.451	-0.621
	(0.090)		(0.084)	(0.320)	(0.195)
\$100,000 to \$149,999	-0.666*		-0.713**	-0.383	-0.524
	(0.054)		(0.041)	(0.354)	(0.239)
\$150,000 or more	-0.417		-0.503	0.117	0.159
	(0.250)		(0.162)	(0.784)	(0.730)
High school graduate	-0.148		-0.147	0.700	0.751
	(0.860)		(0.863)	(0.407)	(0.373)
Some college but no degree	0.546		0.598	0.972	1.043
	(0.515)		(0.482)	(0.250)	(0.217)
Associate degree in college (2-year)	0.367		0.508	1.114	1.154
	(0.663)		(0.551)	(0.194)	(0.179)
Bachelor's degree in college (4-year)	0.445		0.520	0.991	1.091
	(0.590)		(0.534)	(0.236)	(0.192)
Master's degree	0.435		0.510	0.997	1.059
	(0.604)		(0.549)	(0.243)	(0.215)
Professional degree (JD, MD)	1.231		1.306	1.367	1.479
	(0.191)		(0.170)	(0.174)	(0.146)
Doctoral degree	-0.447		-0.323	-0.0375	-0.135
	(0.706)		(0.794)	(0.972)	(0.897)
Female	0.511***		0.444***	0.346**	0.433***
	(0.000)		(0.001)	(0.020)	(0.006)
Student	0.0106		0.0674	0.128	-0.00172
	(0.966)		(0.793)	(0.669)	(0.995)
U1_right		0.123	0.132	-0.0721	-0.0488
		(0.403)	(0.390)	(0.657)	(0.771)
U2_right		0.00691	0.0297	-0.0459	-0.101
		(0.962)	(0.840)	(0.776)	(0.550)
U3_right		1.062***	1.014***	0.825***	0.720**
		(0.000)	(0.000)	(0.008)	(0.027)
U4_right		-0.118	-0.150	-0.188	-0.199
		(0.370)	(0.278)	(0.221)	(0.215)
U5_right		-0.240	-0.241	-0.328*	-0.268
		(0.111)	(0.127)	(0.060)	(0.140)
U6_right		0.232	0.271	0.280	0.237
		(0.275)	(0.231)	(0.258)	(0.364)
U7_right		0.213	0.162	0.147	0.128
		(0.267)	(0.418)	(0.504)	(0.578)
U8_right		-0.106	-0.0798	-0.00384	0.0421
		(0.619)	(0.711)	(0.987)	(0.862)
U9_right		-0.246*	-0.241*	-0.235	-0.315**
		(0.075)	(0.090)	(0.125)	(0.044)
White				0.0398	-0.0314
				(0.819)	(0.860)
Political Scale				-0.414***	-0.395***
				(0.000)	(0.000)
In full or part time employment				-0.171	-0.266
				(0.305)	(0.125)
Republican				-0.605**	-0.601**
				(0.011)	(0.014)
Democrat				0.321*	0.392**
				(0.087)	(0.043)
religion_importance				0.0235	0.0274
				(0.717)	(0.684)
q1_graph_right					-0.0282
					(0.924)
q2_graph_right					0.0367
					(0.831)
q3_graph_right					0.147
					(0.356)
climate_U1right					0.0735
					(0.797)
right_GHGs					0.125
					(0.191)
climate_U3right					0.274*
					(0.081)
climate_U4right					0.187
					(0.268)
climate_U5right					0.493***
					(0.002)
arousal					0.00318
					(0.385)
pleasure					-0.00440
					(0.256)
Observations	952	959	952	943	925
Pseudo R^2	0.015	0.013	0.027	0.124	0.136
chi2	36.44	31.79	69.66	270.8	297.0

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A.7: Understanding determinants per question

	(1) U1_right	(2) U1_right	(3) U1_right	(4) U2_right	(5) U2_right	(6) U2_right	(7) U3_score	(8) U3_score	(9) U3_score
treatment	-0.0651	-0.0630	-0.0718	0.217	0.227	0.201	0.176	0.173	0.156
	(0.643)	(0.660)	(0.632)	(0.119)	(0.109)	(0.170)	(0.132)	(0.141)	(0.203)
Age	-0.00585	-0.00492	-0.00140	-0.0138***	-0.0120**	-0.00960*	0.000845	0.000866	0.00197
	(0.205)	(0.331)	(0.799)	(0.003)	(0.017)	(0.067)	(0.830)	(0.840)	(0.664)
$10,000 to $19,999	-0.0423	-0.123	0.0886	-0.410	-0.529	-0.491	-0.425	-0.521	-0.332
	(0.909)	(0.748)	(0.827)	(0.288)	(0.178)	(0.218)	(0.232)	(0.148)	(0.352)
$20,000 to $29,999	0.172	0.213	0.269	-0.102	-0.169	-0.302	0.392	0.339	0.403
	(0.615)	(0.546)	(0.461)	(0.771)	(0.638)	(0.424)	(0.226)	(0.303)	(0.220)
$30,000 to $39,999	0.296	0.272	0.383	-0.370	-0.416	-0.433	0.0368	0.0175	0.0528
	(0.395)	(0.448)	(0.293)	(0.300)	(0.253)	(0.245)	(0.906)	(0.956)	(0.866)
$40,000 to $49,999	0.390	0.291	0.488	-0.00782	-0.0813	-0.0116	0.426	0.395	0.510
	(0.282)	(0.435)	(0.214)	(0.984)	(0.835)	(0.977)	(0.188)	(0.239)	(0.132)
$50,000 to $59,999	0.0320	0.0707	0.115	-0.246	-0.293	-0.391	0.202	0.193	0.233
	(0.932)	(0.853)	(0.772)	(0.526)	(0.458)	(0.336)	(0.579)	(0.599)	(0.544)
$60,000 to $69,999	-0.0409	-0.118	-0.111	-0.0945	-0.194	-0.293	0.425	0.384	0.393
	(0.912)	(0.760)	(0.783)	(0.808)	(0.630)	(0.474)	(0.191)	(0.247)	(0.236)
$70,000 to $79,999	0.107	0.167	0.110	-0.205	-0.290	-0.417	-0.0373	-0.0175	-0.0308
	(0.791)	(0.689)	(0.792)	(0.624)	(0.493)	(0.330)	(0.916)	(0.961)	(0.932)
$80,000 to $89,999	0.126	0.0651	0.0367	-0.171	-0.214	-0.446	0.415	0.418	0.402
	(0.751)	(0.876)	(0.930)	(0.682)	(0.623)	(0.313)	(0.208)	(0.217)	(0.231)
$90,000 to $99,999	-0.180	-0.157	-0.0358	0.220	0.121	0.171	0.301	0.313	0.354
	(0.661)	(0.714)	(0.936)	(0.616)	(0.788)	(0.717)	(0.413)	(0.411)	(0.365)
$100,000 to $149,999	0.328	0.403	0.454	-0.103	-0.148	-0.187	0.445	0.463	0.459
	(0.346)	(0.266)	(0.225)	(0.776)	(0.693)	(0.634)	(0.153)	(0.149)	(0.152)
$150,000 or more	0.0147	0.00580	0.150	-0.173	-0.210	-0.0944	0.326	0.347	0.426
	(0.969)	(0.988)	(0.721)	(0.666)	(0.612)	(0.826)	(0.323)	(0.302)	(0.213)
High school graduate	1.317	1.317	1.337*	-0.0110	-0.0149	-0.0898	-0.331	-0.323	-0.333
	(0.137)	(0.137)	(0.092)	(0.989)	(0.987)	(0.915)	(0.547)	(0.572)	(0.420)
Some college but no degree	1.513*	1.411	1.332*	0.327	0.239	0.0892	0.232	0.186	0.135
	(0.086)	(0.109)	(0.090)	(0.685)	(0.790)	(0.915)	(0.669)	(0.743)	(0.735)
Associate degree in college (2-year)	1.446	1.303	1.269	0.126	-0.0406	-0.147	0.274	0.149	0.134
	(0.105)	(0.143)	(0.113)	(0.878)	(0.964)	(0.862)	(0.625)	(0.797)	(0.753)
Bachelor's degree in college (4-year)	1.626*	1.528*	1.362*	0.357	0.225	0.0718	0.0905	0.0199	-0.0430
	(0.063)	(0.079)	(0.079)	(0.655)	(0.801)	(0.931)	(0.867)	(0.972)	(0.914)
Master's degree	1.465*	1.374	1.157	0.444	0.344	0.121	0.0568	0.0190	-0.107
	(0.099)	(0.121)	(0.146)	(0.586)	(0.704)	(0.885)	(0.918)	(0.974)	(0.795)
Professional degree (JD, MD)	2.698**	2.593**	2.507**	0.413	0.254	0.116	0.508	0.401	0.223
	(0.012)	(0.018)	(0.014)	(0.654)	(0.801)	(0.903)	(0.472)	(0.584)	(0.728)
Doctoral degree	0.404	0.414	0.205	0.705	0.676	0.391	-0.473	-0.462	-0.589
	(0.712)	(0.713)	(0.854)	(0.513)	(0.554)	(0.726)	(0.561)	(0.553)	(0.401)
Female	-0.370***	-0.394***	-0.282*	-0.0301	-0.0607	0.0592	0.0992	0.0691	0.185
	(0.008)	(0.006)	(0.070)	(0.829)	(0.673)	(0.700)	(0.411)	(0.571)	(0.154)
Student	0.212	0.234	0.110	0.249	0.250	0.0846	0.194	0.134	-0.0679
	(0.509)	(0.499)	(0.761)	(0.465)	(0.498)	(0.818)	(0.488)	(0.664)	(0.824)
White		0.196	0.0501		-0.0932	-0.240		0.126	0.0145
		(0.251)	(0.782)		(0.589)	(0.175)		(0.380)	(0.925)
Political Scale		-0.0251	-0.0229		0.0267	0.0264		0.00268	0.0139
		(0.648)	(0.690)		(0.618)	(0.642)		(0.956)	(0.782)
In full or part time employment		0.00115	0.0896		-0.0416	-0.0732		-0.131	-0.152
		(0.994)	(0.602)		(0.797)	(0.666)		(0.354)	(0.304)
Republican		-0.195	-0.264		0.202	0.247		0.0636	0.0297
		(0.415)	(0.300)		(0.383)	(0.309)		(0.762)	(0.888)
Democrat		0.127	0.0948		0.539***	0.571***		0.411**	0.380**
		(0.518)	(0.646)		(0.006)	(0.005)		(0.013)	(0.030)
religion_importance		-0.165**	-0.0716		-0.187***	-0.130*		-0.0741	0.0112
		(0.012)	(0.319)		(0.004)	(0.058)		(0.198)	(0.856)
q1_graph_right			0.209			0.579**			0.659***
			(0.471)			(0.032)			(0.001)
q2_graph_right			0.891***			0.667***			0.434***
			(0.000)			(0.000)			(0.001)
q3_graph_right			-0.353**			-0.233			-0.161
			(0.021)			(0.124)			(0.217)
climate_U1right			0.411			0.0241			0.472**
			(0.161)			(0.932)			(0.012)
right_GHGs			0.142			0.166*			0.209***
			(0.103)			(0.054)			(0.005)
climate_U3right			-0.100			-0.226			-0.0508
			(0.532)			(0.141)			(0.690)
climate_U4right			0.141			0.150			-0.0185
			(0.388)			(0.342)			(0.884)
climate_U5right			-0.0447			-0.181			0.00391
			(0.777)			(0.244)			(0.976)
arousal			-0.00336			0.00504			-0.000381
			(0.311)			(0.141)			(0.897)
pleasure			-0.000734			-0.00384			-0.00273
			(0.837)			(0.295)			(0.406)
Constant	-0.622	-0.442	-1.542	0.927	0.963	0.0321			
	(0.506)	(0.639)	(0.102)	(0.285)	(0.318)	(0.974)			
Observations	952	943	925	952	943	925	952	943	925
Pseudo R^2	0.024	0.041	0.085	0.021	0.036	0.068	0.010	0.015	0.028
chi2	27.28	44.20	90.14	24.73	43.25	81.53	32.81	48.98	120.7

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A.8: Understanding determinants overall

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	U_tot	U_tot	U_tot	U_tot	Scores for component 1	Scores for component 1	Scores for component 1	Scores for component 1
treatment	0.158	0.167	0.162	0.139	0.0982	0.115	0.120	0.0928
	(0.164)	(0.149)	(0.163)	(0.252)	(0.359)	(0.287)	(0.264)	(0.388)
Age		-0.00397	-0.00296	-0.000926		-0.00260	-0.00209	-0.0000754
		(0.312)	(0.491)	(0.836)		(0.480)	(0.590)	(0.985)
$10,000 to $19,999		-0.379	-0.497	-0.284		-0.414	-0.513	-0.379
		(0.306)	(0.183)	(0.446)		(0.236)	(0.145)	(0.266)
$20,000 to $29,999		0.313	0.265	0.290		0.316	0.279	0.267
		(0.329)	(0.416)	(0.385)		(0.283)	(0.349)	(0.362)
$30,000 to $39,999		0.0549	0.0109	0.0531		0.130	0.0887	0.105
		(0.865)	(0.973)	(0.871)		(0.662)	(0.767)	(0.719)
$40,000 to $49,999		0.382	0.338	0.471		0.497^{*}	0.427	0.498^{*}
		(0.240)	(0.314)	(0.166)		(0.088)	(0.153)	(0.088)
$50,000 to $59,999		0.154	0.144	0.165		0.142	0.132	0.141
		(0.679)	(0.698)	(0.675)		(0.669)	(0.692)	(0.671)
$60,000 to $69,999		0.330	0.244	0.231		0.445	0.377	0.324
		(0.326)	(0.474)	(0.501)		(0.152)	(0.238)	(0.301)
$70,000 to $79,999		-0.107	-0.102	-0.169		0.0637	0.0606	0.0133
		(0.763)	(0.773)	(0.634)		(0.850)	(0.857)	(0.968)
$80,000 to $89,999		0.287	0.278	0.210		0.358	0.338	0.256
		(0.382)	(0.415)	(0.538)		(0.256)	(0.299)	(0.417)
$90,000 to $99,999		0.256	0.242	0.315		0.214	0.182	0.218
		(0.500)	(0.540)	(0.441)		(0.551)	(0.615)	(0.545)
$100,000 to $149,999		0.340	0.357	0.349		0.387	0.398	0.371
		(0.266)	(0.259)	(0.277)		(0.184)	(0.181)	(0.205)
$150,000 or more		0.201	0.222	0.334		0.405	0.402	0.465
		(0.544)	(0.507)	(0.330)		(0.184)	(0.196)	(0.130)
High school graduate		-0.0583	-0.0406	-0.0450		-0.128	-0.0993	-0.141
		(0.909)	(0.939)	(0.904)		(0.813)	(0.864)	(0.745)
Some college but no degree		0.493	0.440	0.361		0.371	0.300	0.187
		(0.326)	(0.399)	(0.314)		(0.487)	(0.602)	(0.656)
Associate degree in college (2-year)		0.514	0.360	0.342		0.171	0.0688	-0.00176
		(0.328)	(0.509)	(0.386)		(0.757)	(0.908)	(0.997)
Bachelor's degree in college (4-year)		0.426	0.336	0.244		0.216	0.150	-0.0118
		(0.395)	(0.518)	(0.494)		(0.683)	(0.793)	(0.977)
Master's degree		0.394	0.319	0.152		0.200	0.161	-0.0212
		(0.446)	(0.550)	(0.683)		(0.712)	(0.783)	(0.961)
Professional degree (JD, MD)		0.881	0.750	0.624		0.537	0.414	0.230
		(0.180)	(0.273)	(0.290)		(0.377)	(0.523)	(0.664)
Doctoral degree		-0.258	-0.273	-0.451		-0.363	-0.303	-0.521
		(0.720)	(0.693)	(0.482)		(0.638)	(0.702)	(0.469)
Female		-0.00272	-0.0401	0.0920		0.0644	0.0260	0.122
		(0.982)	(0.738)	(0.465)		(0.563)	(0.816)	(0.278)
Student		0.270	0.254	0.0399		0.209	0.182	0.0106
		(0.364)	(0.435)	(0.900)		(0.405)	(0.499)	(0.968)
White			0.0834	-0.0584			0.167	0.0521
			(0.567)	(0.704)			(0.230)	(0.712)
Political Scale			0.00756	0.0171			-0.0269	-0.0200
			(0.874)	(0.731)			(0.549)	(0.653)
In full or part time employment			-0.0894	-0.0884			-0.0929	-0.0832
			(0.513)	(0.542)			(0.457)	(0.510)
Republican			0.0257	-0.00760			0.0249	-0.0194
			(0.897)	(0.970)			(0.896)	(0.918)
Democrat			0.463^{***}	0.439^{**}			0.324^{**}	0.277^{*}
			(0.005)	(0.012)			(0.036)	(0.073)
religion_importance			-0.129^{**}	-0.0350			-0.108^{**}	-0.0370
			(0.019)	(0.548)			(0.037)	(0.473)
q1_graph_right				0.656^{***}				0.529^{***}
				(0.001)				(0.009)
q2_graph_right				0.654^{***}				0.545^{***}
				(0.000)				(0.000)
q3_graph_right				-0.251^{**}				-0.126
				(0.049)				(0.254)
climate_U1right				0.439^{**}				0.349
				(0.037)				(0.106)
right_GHGs				0.215^{***}				0.202^{***}
				(0.002)				(0.002)
climate_U3right				-0.0878				0.000532
				(0.489)				(0.996)
climate_U4right				0.0370				0.116
				(0.769)				(0.291)
climate_U5right				-0.0433				-0.00807
				(0.730)				(0.942)
arousal				0.000370				-0.000829
				(0.896)				(0.744)
pleasure				-0.00249				-0.000796
				(0.446)				(0.783)
Constant					-0.0506	-0.411	-0.363	-1.676^{***}
					(0.498)	(0.486)	(0.565)	(0.004)
Observations	959	952	943	925	959	952	943	925
(Pseudo) R^2	0.000	0.008	0.015	0.031	0.0009	0.0349	0.0629	0.1181
chi2	1.934	31.62	56.81	144.4				

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A.9: Understanding determinants overall

	(1) Scores for component 2	(2) Scores for component 2	(3) Scores for component 2	(4) Scores for component 2	(5) Scores for component 3	(6) Scores for component 3	(7) Scores for component 3	(8) Scores for component 3
treatment	0.0156	0.0101	0.00470	-0.00322	0.0229	0.0332	0.0261	0.00621
	(0.827)	(0.892)	(0.950)	(0.966)	(0.723)	(0.611)	(0.690)	(0.925)
Age		0.000419	0.000293	-0.0000226		0.00784***	0.00729***	0.00562**
		(0.864)	(0.908)	(0.993)		(0.000)	(0.002)	(0.021)
$10,000 to $19,999		0.188	0.192	0.212		-0.112	-0.0915	-0.125
		(0.345)	(0.334)	(0.289)		(0.502)	(0.579)	(0.453)
$20,000 to $29,999		0.148	0.141	0.159		-0.0464	-0.0221	0.00308
		(0.390)	(0.416)	(0.354)		(0.757)	(0.883)	(0.984)
$30,000 to $39,999		-0.0749	-0.0595	-0.0237		0.0872	0.0955	0.0970
		(0.677)	(0.742)	(0.895)		(0.553)	(0.517)	(0.520)
$40,000 to $49,999		0.000340	-0.00551	0.0551		0.0641	0.0754	0.0587
		(0.998)	(0.976)	(0.764)		(0.677)	(0.626)	(0.709)
$50,000 to $59,999		0.0795	0.0680	0.114		0.00149	0.0301	0.0473
		(0.681)	(0.726)	(0.558)		(0.993)	(0.858)	(0.784)
$60,000 to $69,999		-0.119	-0.122	-0.0699		0.0828	0.113	0.124
		(0.522)	(0.517)	(0.707)		(0.598)	(0.484)	(0.458)
$70,000 to $79,999		-0.0409	-0.0283	-0.0255		0.0649	0.0793	0.107
		(0.839)	(0.890)	(0.899)		(0.730)	(0.678)	(0.579)
$80,000 to $89,999		0.194	0.217	0.252		0.168	0.189	0.214
		(0.356)	(0.303)	(0.237)		(0.379)	(0.321)	(0.275)
$90,000 to $99,999		0.201	0.222	0.223		0.112	0.132	0.0783
		(0.344)	(0.297)	(0.302)		(0.529)	(0.469)	(0.653)
$100,000 to $149,999		0.0641	0.0441	0.0768		0.0336	0.0600	0.0504
		(0.721)	(0.805)	(0.667)		(0.818)	(0.684)	(0.740)
$150,000 or more		-0.167	-0.171	-0.164		0.185	0.211	0.181
		(0.396)	(0.388)	(0.413)		(0.264)	(0.209)	(0.302)
High school graduate		0.0603	0.0689	0.0115		-0.350	-0.343	-0.380
		(0.901)	(0.883)	(0.980)		(0.307)	(0.348)	(0.296)
Some college but no degree		0.195	0.244	0.173		-0.425	-0.428	-0.425
		(0.684)	(0.598)	(0.708)		(0.210)	(0.238)	(0.238)
Associate degree in college (2-year)		0.463	0.470	0.413		-0.435	-0.392	-0.403
		(0.337)	(0.315)	(0.379)		(0.212)	(0.292)	(0.279)
Bachelor's degree in college (4-year)		0.252	0.266	0.224		-0.442	-0.415	-0.398
		(0.596)	(0.564)	(0.626)		(0.187)	(0.246)	(0.265)
Master's degree		0.197	0.223	0.143		-0.520	-0.483	-0.447
		(0.683)	(0.634)	(0.758)		(0.129)	(0.187)	(0.222)
Professional degree (JD, MD)		0.586	0.624	0.545		-0.582	-0.555	-0.559
		(0.283)	(0.239)	(0.299)		(0.182)	(0.217)	(0.211)
Doctoral degree		0.290	0.279	0.294		-0.318	-0.282	-0.237
		(0.576)	(0.580)	(0.566)		(0.511)	(0.580)	(0.647)
Female		-0.187**	-0.191***	-0.161**		0.231***	0.237***	0.212***
		(0.010)	(0.010)	(0.039)		(0.000)	(0.000)	(0.002)
Student		0.0170	-0.0349	-0.0613		-0.153	-0.153	-0.142
		(0.914)	(0.837)	(0.723)		(0.247)	(0.299)	(0.343)
White			-0.114	-0.0876			0.110	0.142*
			(0.191)	(0.324)			(0.172)	(0.074)
Political Scale			0.0497*	0.0446			-0.0214	-0.0203
			(0.074)	(0.113)			(0.368)	(0.397)
In full or part time employment			-0.0415	-0.0490			-0.0242	-0.0349
			(0.617)	(0.563)			(0.751)	(0.649)
Republican			0.0364	0.0797			-0.177	-0.170
			(0.776)	(0.527)			(0.128)	(0.157)
Democrat			0.153	0.146			-0.202**	-0.192**
			(0.120)	(0.152)			(0.019)	(0.027)
religion_importance			-0.00597	0.0167			0.0436	0.0274
			(0.863)	(0.643)			(0.166)	(0.405)
q1_graph_right				0.205				-0.0374
				(0.142)				(0.788)
q2_graph_right				0.0180				-0.223***
				(0.826)				(0.004)
q3_graph_right				-0.164**				0.123*
				(0.035)				(0.063)
climate_U1right				0.0427				0.109
				(0.791)				(0.466)
right_GHGs				0.0249				-0.0234
				(0.558)				(0.563)
climate_U3right				-0.181**				0.0235
				(0.017)				(0.735)
climate_U4right				-0.117				0.0344
				(0.129)				(0.628)
climate_U5right				-0.0263				0.00712
				(0.728)				(0.917)
arousal				-0.00101				-0.000289
				(0.577)				(0.858)
pleasure				-0.00186				-0.00146
				(0.338)				(0.402)
Constant	-0.00801	-0.209	-0.321	-0.223	-0.0118	-0.0780	-0.0208	0.173
	(0.879)	(0.682)	(0.525)	(0.676)	(0.797)	(0.831)	(0.958)	(0.682)
Observations	959	952	943	925	959	952	943	925
Adjusted R^2	0.0000	0.0277	0.0359	0.0558	0.0001	0.0410	0.0501	0.0670

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A.10: Time in policy and perception determinants

	(1) time_policy	(2) time_policy	(3) time_policy	(4) time_perception	(5) time_perception	(6) time_perception
treatment	-3.034	-1.569	-1.050	2.310	2.582	2.788
	(0.694)	(0.838)	(0.892)	(0.379)	(0.325)	(0.355)
Age	1.338***	1.448***	1.543***	0.289***	0.327***	0.332***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)	(0.003)
$10,000 to $19,999	-5.802	-6.166	0.454	3.411	4.465	4.652
	(0.814)	(0.801)	(0.985)	(0.698)	(0.607)	(0.581)
$20,000 to $29,999	4.364	3.122	-1.559	-1.430	-0.327	0.461
	(0.851)	(0.892)	(0.945)	(0.783)	(0.950)	(0.934)
$30,000 to $39,999	5.280	6.509	-0.228	1.456	2.560	2.318
	(0.823)	(0.780)	(0.992)	(0.825)	(0.704)	(0.743)
$40,000 to $49,999	11.62	13.15	5.094	0.0606	1.662	1.643
	(0.634)	(0.592)	(0.834)	(0.993)	(0.810)	(0.826)
$50,000 to $59,999	-4.641	-8.040	-6.867	-5.091	-5.220	-4.321
	(0.864)	(0.766)	(0.795)	(0.322)	(0.308)	(0.402)
$60,000 to $69,999	13.90	12.61	7.986	-2.536	-1.207	-1.521
	(0.598)	(0.638)	(0.766)	(0.690)	(0.854)	(0.820)
$70,000 to $79,999	-4.245	-1.987	-4.661	-9.486*	-8.333	-7.699
	(0.874)	(0.941)	(0.861)	(0.088)	(0.151)	(0.177)
$80,000 to $89,999	-0.381	3.499	0.451	-8.881	-6.779	-4.793
	(0.989)	(0.901)	(0.987)	(0.108)	(0.218)	(0.393)
$90,000 to $99,999	-14.94	-18.39	-24.27	-8.760	-7.621	-7.272
	(0.552)	(0.472)	(0.334)	(0.131)	(0.210)	(0.251)
$100,000 to $149,999	1.559	2.161	-6.620	-2.879	-1.591	-0.970
	(0.953)	(0.935)	(0.795)	(0.582)	(0.765)	(0.858)
$150,000 or more	-41.20*	-36.61	-47.86*	-6.905	-5.299	-4.347
	(0.098)	(0.141)	(0.061)	(0.310)	(0.438)	(0.575)
High school graduate	-11.91	-3.506	-2.978	9.594***	10.68***	11.86**
	(0.653)	(0.873)	(0.905)	(0.009)	(0.009)	(0.015)
Some college but no degree	3.691	9.018	1.835	10.10***	10.70***	11.49**
	(0.889)	(0.685)	(0.941)	(0.002)	(0.009)	(0.023)
Associate degree in college (2-year)	30.93	34.85	29.21	16.91**	17.81**	18.39**
	(0.276)	(0.155)	(0.284)	(0.028)	(0.011)	(0.010)
Bachelor's degree in college (4-year)	8.097	12.12	7.875	6.861**	7.121**	7.880*
	(0.755)	(0.570)	(0.745)	(0.012)	(0.035)	(0.059)
Master's degree	8.689	10.71	7.353	12.18***	12.82***	12.85**
	(0.751)	(0.645)	(0.776)	(0.001)	(0.005)	(0.014)
Professional degree (JD, MD)	-7.578	-5.984	-19.87	14.32	14.40	13.76
	(0.800)	(0.823)	(0.475)	(0.309)	(0.310)	(0.344)
Doctoral degree	16.38	15.04	26.13	11.37	10.32	11.67
	(0.584)	(0.578)	(0.396)	(0.427)	(0.486)	(0.462)
Female	11.80	9.894	14.22*	-0.335	-0.351	-0.545
	(0.117)	(0.196)	(0.079)	(0.891)	(0.891)	(0.839)
Student	27.10	25.78	25.76	-2.937	-3.381	-3.507
	(0.239)	(0.279)	(0.265)	(0.455)	(0.523)	(0.557)
White		-16.73*	-16.93*		-5.405*	-5.156*
		(0.077)	(0.089)		(0.053)	(0.068)
Political Scale		3.285	3.126		0.0601	0.272
		(0.239)	(0.267)		(0.958)	(0.816)
In full or part time employment		-0.288	2.514		-0.505	-0.666
		(0.975)	(0.775)		(0.893)	(0.863)
Republican		-2.024	-2.088		-2.045	-2.540
		(0.855)	(0.850)		(0.547)	(0.449)
Democrat		29.85***	18.54*		-1.920	-2.092
		(0.004)	(0.083)		(0.650)	(0.632)
religion_importance		2.295	5.365		-0.865	-0.873
		(0.554)	(0.176)		(0.399)	(0.439)
U1_right			16.81**			0.354
			(0.029)			(0.896)
U2_right			14.25			0.339
			(0.102)			(0.915)
U3_right			17.67			11.68**
			(0.347)			(0.025)
U4_right			2.330			-1.717
			(0.792)			(0.557)
U5_right			3.512			0.797
			(0.729)			(0.796)
U6_right			13.90			-8.199*
			(0.253)			(0.075)
U7_right			7.674			-1.218
			(0.457)			(0.763)
U8_right			-0.585			3.584
			(0.960)			(0.451)
U9_right			24.20***			1.198
			(0.002)			(0.616)
q1_graph_right			-10.02			-1.755
			(0.554)			(0.760)
q2_graph_right			-6.419			-1.746
			(0.457)			(0.507)
q3_graph_right			-19.23**			-1.032
			(0.017)			(0.708)
climate_U1right			9.877			1.823
			(0.456)			(0.672)
right_GHGs			6.732			-0.655
			(0.124)			(0.730)
climate_U3right			-2.575			2.812
			(0.736)			(0.283)
climate_U4right			-10.81			1.516
			(0.206)			(0.617)
climate_U5right			6.741			4.477
			(0.414)			(0.134)
arousal			-0.203			-0.0513
			(0.325)			(0.402)
pleasure			0.554**			-0.00466
			(0.017)			(0.940)
Constant	43.54	19.66	-57.31	10.51	13.61*	7.180
	(0.212)	(0.531)	(0.185)	(0.107)	(0.083)	(0.561)
Observations	952	943	925	952	943	925
Adjusted R^2	0.0560	0.0716	0.1378	0.0339	0.0387	0.0525

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A.11: OLS coefficients deriving from regressions with the time taken by participants to answer the understanding questions (Columns 1-3) and the entire survey (Columns 4-6). The time taken in seconds is the dependent variable and a binary variable is used to measure the impact of being in the treatment group with respect to the control group. The regressions are ran with robust standard errors controlling for: a reduced set of demographics (Columns 1 and 4); full demographics (Columns 2 and 5); full demographics, graph literacy, climate literacy and the perceived levels of arousal and pleasure of the participants elicited by the palette with the colors of the figure participants see (Columns 3 and 6).

	(1) time_understanding	(2) time_understanding	(3) time_understanding	(4) Time: full survey	(5) Time: full survey	(6) Time: full survey
treatment	-25.12**	-22.96*	-26.15**	112.0	108.4	107.8
	(0.037)	(0.057)	(0.037)	(0.208)	(0.178)	(0.190)
Age	3.613***	3.596***	3.632***	-1.685	0.101	0.780
	(0.000)	(0.000)	(0.000)	(0.741)	(0.980)	(0.820)
Less than $10,000	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)
$10,000 to $19,999	-3.713	1.506	5.204	-79.62	6.980	46.76
	(0.890)	(0.956)	(0.851)	(0.250)	(0.947)	(0.730)
$20,000 to $29,999	79.77**	87.18**	85.41**	108.2	192.0	210.0
	(0.030)	(0.019)	(0.024)	(0.258)	(0.131)	(0.142)
$30,000 to $39,999	16.56	26.87	21.13	500.0	571.9	603.0
	(0.533)	(0.309)	(0.437)	(0.372)	(0.339)	(0.336)
$40,000 to $49,999	19.02	30.03	24.19	-49.27	44.87	83.56
	(0.425)	(0.209)	(0.341)	(0.491)	(0.552)	(0.428)
$50,000 to $59,999	11.66	14.96	20.04	-81.11	-30.56	-24.12
	(0.676)	(0.594)	(0.482)	(0.213)	(0.681)	(0.772)
$60,000 to $69,999	37.32	48.35*	43.40	62.36	130.0	158.4
	(0.162)	(0.080)	(0.127)	(0.558)	(0.232)	(0.174)
$70,000 to $79,999	1.068	14.01	12.90	-51.51	15.39	6.208
	(0.971)	(0.644)	(0.674)	(0.499)	(0.837)	(0.940)
$80,000 to $89,999	11.89	26.24	20.42	-157.4	-39.63	-1.974
	(0.663)	(0.342)	(0.478)	(0.130)	(0.637)	(0.983)
$90,000 to $99,999	-3.263	1.832	5.164	-29.36	38.97	72.03
	(0.904)	(0.947)	(0.856)	(0.831)	(0.798)	(0.653)
$100,000 to $149,999	23.79	33.56	28.21	-141.6	-89.88	-39.29
	(0.327)	(0.176)	(0.277)	(0.259)	(0.437)	(0.666)
$150,000 or more	-23.02	-5.779	-3.084	-177.7	-86.26	-62.59
	(0.352)	(0.820)	(0.911)	(0.212)	(0.482)	(0.569)
Female	-10.91	-12.03	-7.988	165.3	188.0	191.4
	(0.342)	(0.313)	(0.550)	(0.198)	(0.220)	(0.243)
Less than high school degree	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)
High school graduate	-129.9	-108.4	-93.48	-56.73	0.996	-43.72
	(0.243)	(0.295)	(0.350)	(0.731)	(0.996)	(0.811)
Some college but no degree	-111.8	-89.03	-83.07	-30.35	45.77	-12.89
	(0.315)	(0.391)	(0.412)	(0.851)	(0.827)	(0.942)
Associate degree in college (2-year)	-146.7	-122.0	-117.0	49.72	140.9	80.90
	(0.186)	(0.237)	(0.242)	(0.790)	(0.553)	(0.686)
Bachelor's degree in college (4-year)	-155.8	-133.7	-128.6	-6.172	43.55	-16.89
	(0.157)	(0.192)	(0.195)	(0.974)	(0.854)	(0.928)
Master's degree	-128.6	-107.9	-101.3	519.9	572.7	489.5
	(0.245)	(0.297)	(0.314)	(0.394)	(0.373)	(0.379)
Professional degree (JD, MD)	-177.5	-157.4	-161.7	172.2	240.3	200.0
	(0.115)	(0.137)	(0.117)	(0.531)	(0.470)	(0.494)
Doctoral degree	-188.5	-175.9	-163.1	-63.35	-131.7	-166.1
	(0.101)	(0.105)	(0.119)	(0.786)	(0.608)	(0.439)
familiar with IPCC	6.982			2.924		
	(0.513)			(0.934)		
White		-35.41**	-39.14***		-324.5*	-326.7*
		(0.015)	(0.009)		(0.090)	(0.082)
Political Scale		5.487	5.853		35.94	30.66
		(0.326)	(0.325)		(0.203)	(0.242)
In full or part time employment		-20.04	-18.41		24.19	45.48
		(0.192)	(0.248)		(0.738)	(0.601)
Student		-30.10	-43.79**		-67.01	-42.82
		(0.178)	(0.048)		(0.661)	(0.772)
Republican		-31.54	-38.30**		-285.1	-265.9
		(0.100)	(0.050)		(0.204)	(0.226)
Democrat		15.98	8.451		-168.8	-161.8
		(0.444)	(0.690)		(0.378)	(0.387)
religion importance		8.335	9.190		14.44	22.95
		(0.103)	(0.109)		(0.372)	(0.259)
q1_graph_right			28.28			61.65
			(0.217)			(0.712)
q2_graph_right			-5.626			117.5
			(0.720)			(0.471)
q3_graph_right			-19.06			-174.4
			(0.129)			(0.316)
climate_U1right			-16.51			157.1
			(0.656)			(0.307)
right_GHGs			22.82***			-86.44
			(0.001)			(0.347)
climate_U3right			27.39**			-120.5
			(0.028)			(0.309)
climate_U4right			19.59			-19.67
			(0.143)			(0.713)
climate_U5right			-4.295			-77.90
			(0.741)			(0.396)
arousal			0.0684			0.121
			(0.822)			(0.924)
pleasure			0.117			0.0687
			(0.702)			(0.957)
Constant	271.1**	256.7**	205.1*	353.4**	393.0*	391.2
	(0.017)	(0.020)	(0.094)	(0.041)	(0.093)	(0.141)
Observations	951	943	925	951	943	925
Adjusted R^2	0.0842	0.1252	0.1388	0.1083	0.1696	0.1801

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.A.2 Study I Follow Up

Besides the experiments described in the article, we also carried out a follow up study to Study I. The goal of this follow-up was testing whether the choice of colour affected learning. For this reason, at the end of Study I we gave respondents the possibility to watch a short video explaining how to read the figure that they had been shown during the experiment. In particular, one week after Study I, we invited the respondents who participated in Study I to take part in a second survey. All participants were informed of this possibility at the beginning of the first experiment. As in Study I, half of the respondents were randomly assigned to seeing the original colours from the IPCC Report (original figure), the other half was randomly assigned to see a figure in which all the increases of extreme events were marked in red and the decreases in green (treatment figure) (see Fig. 2.1). As a result, we had a 2x2 design with respondents divided in four groups. The first group saw during both rounds the original figure. The second group saw the original figure during the first round and the treatment figure in the second round. The third group saw the treatment figure in the first round and the original figure in the second round. Last, the fourth group so the treatment figure in both rounds.

We then tested respondents understanding of the figure by asking questions that were very similar – but not identical – to those included in the Study I. However, we found no significant effects on any of the variables of interest.

Here we report the full regression tables relatives to the follow up to first experiment.

Table 2.A.12: Globes understanding determinants

	(1)	(2)	(3)	(4)	(5)	(6)
	q1_globes_right	q1_globes_right	q1_globes_right	q2_globes_right	q2_globes_right	q2_globes_right
main						
treatment	0.201	0.185	0.185	0.0964	0.0616	-0.0595
	(0.167)	(0.240)	(0.277)	(0.514)	(0.701)	(0.742)
Age	-0.0134***	-0.0197***	-0.0212***	-0.000777	-0.00169	-0.00104
	(0.005)	(0.001)	(0.001)	(0.873)	(0.772)	(0.871)
\$10,000 to \$19,999	0.479	0.493	0.824*	0.255	0.168	0.624
	(0.199)	(0.234)	(0.089)	(0.495)	(0.678)	(0.168)
\$20,000 to \$29,999	0.279	0.212	0.148	0.597*	0.536	0.531
	(0.418)	(0.581)	(0.733)	(0.096)	(0.165)	(0.223)
\$30,000 to \$39,999	0.616*	0.635	0.817*	0.271	0.134	0.253
	(0.077)	(0.103)	(0.073)	(0.441)	(0.723)	(0.563)
\$40,000 to \$49,999	0.592	0.560	0.393	0.530	0.425	0.273
	(0.114)	(0.183)	(0.398)	(0.154)	(0.293)	(0.553)
\$50,000 to \$59,999	-0.0130	0.0417	-0.0286	0.604	0.733*	0.954*
	(0.972)	(0.920)	(0.950)	(0.118)	(0.086)	(0.063)
\$60,000 to \$69,999	0.514	0.485	0.513	0.785**	0.648	0.720
	(0.170)	(0.235)	(0.268)	(0.047)	(0.117)	(0.133)
\$70,000 to \$79,999	0.0927	-0.0404	0.0171	0.376	0.402	0.486
	(0.815)	(0.925)	(0.971)	(0.363)	(0.380)	(0.333)
\$80,000 to \$89,999	0.932**	0.686	0.693	0.994**	0.831*	0.860
	(0.034)	(0.136)	(0.163)	(0.024)	(0.085)	(0.121)
\$90,000 to \$99,999	0.0210	0.117	0.0298	0.433	0.288	0.247
	(0.959)	(0.792)	(0.951)	(0.312)	(0.529)	(0.615)
\$100,000 to \$149,999	0.335	0.309	0.108	0.714**	0.610	0.512
	(0.338)	(0.434)	(0.806)	(0.048)	(0.110)	(0.236)
\$150,000 or more	0.444	0.349	0.172	0.525	0.510	0.397
	(0.264)	(0.446)	(0.727)	(0.189)	(0.258)	(0.435)
High school graduate	1.203	1.163	1.220	-1.076	-1.202	-1.327
	(0.111)	(0.107)	(0.155)	(0.330)	(0.326)	(0.283)
Some college but no degree	1.866**	1.823**	1.799**	-0.972	-1.217	-1.575
	(0.013)	(0.011)	(0.035)	(0.377)	(0.315)	(0.196)
Associate degree in college (2-year)	1.584**	1.486**	1.501*	-0.928	-1.148	-1.368
	(0.037)	(0.043)	(0.088)	(0.402)	(0.349)	(0.268)
Bachelor's degree in college (4-year)	2.086***	1.990***	2.139**	-0.888	-1.079	-1.253
	(0.005)	(0.005)	(0.012)	(0.416)	(0.372)	(0.302)
Master's degree	2.093***	2.078***	2.248**	-0.734	-0.815	-0.938
	(0.006)	(0.005)	(0.011)	(0.507)	(0.506)	(0.448)
Professional degree (JD, MD)	2.162**	2.007**	1.779*	-0.157	-0.492	-0.839
	(0.016)	(0.030)	(0.078)	(0.901)	(0.723)	(0.531)
Doctoral degree	2.667**	3.057***	3.803***	-0.891	-0.859	-0.450
	(0.017)	(0.004)	(0.002)	(0.489)	(0.539)	(0.778)
Female	-0.301**	-0.163	-0.158	0.120	0.265	0.271
	(0.039)	(0.312)	(0.371)	(0.423)	(0.120)	(0.156)
Student	-0.0841	-0.644	-0.710	0.671*	0.278	0.276
	(0.805)	(0.114)	(0.110)	(0.070)	(0.505)	(0.535)
White		0.285	0.333		0.359*	0.415**
		(0.134)	(0.107)		(0.055)	(0.050)
Political Scale		-0.0669	-0.0812		-0.0182	-0.00983
		(0.274)	(0.199)		(0.770)	(0.881)
In full or part time employment		-0.405**	-0.402**		-0.498***	-0.519**
		(0.022)	(0.043)		(0.007)	(0.012)
Republican		0.451*	0.528*		0.0619	0.0440
		(0.080)	(0.074)		(0.812)	(0.880)
Democrat		0.0433	-0.196		0.229	0.00430
		(0.842)	(0.406)		(0.300)	(0.986)
religion_importance		-0.0935	-0.0761		-0.168**	-0.181**
		(0.221)	(0.361)		(0.029)	(0.035)
q1_graph_right		0.308	0.104		0.236	-0.0781
		(0.305)	(0.776)		(0.437)	(0.828)
q2_graph_right		0.570***	0.266		0.512***	0.162
		(0.001)	(0.148)		(0.003)	(0.422)
q3_graph_right		-0.282*	-0.214		-0.0689	0.0256
		(0.079)	(0.229)		(0.676)	(0.888)
climate_U1right		0.590*	0.531		0.328	0.225
		(0.058)	(0.103)		(0.236)	(0.481)
right_GHGs		0.401***	0.336***		0.352***	0.287**
		(0.000)	(0.001)		(0.000)	(0.010)
climate_U3right		-0.245	-0.241		0.0245	0.0126
		(0.137)	(0.181)		(0.884)	(0.948)
climate_U4right		0.108	0.0801		0.233	0.195
		(0.531)	(0.667)		(0.186)	(0.312)
climate_U5right		0.0806	0.0797		0.232	0.297
		(0.624)	(0.643)		(0.168)	(0.115)
arousal		-0.0137***	-0.0154***		-0.00320	-0.00332
		(0.000)	(0.000)		(0.383)	(0.430)
pleasure		0.00904**	0.0112**		0.00639*	0.00815*
		(0.020)	(0.013)		(0.096)	(0.074)
U1_right			0.716***			0.485**
			(0.000)			(0.014)
U2_right			0.697***			0.774***
			(0.000)			(0.000)
U3_right			0.0745			0.0907
			(0.844)			(0.801)
U4_right			0.209			0.0484
			(0.257)			(0.801)
U5_right			0.330*			0.607***
			(0.088)			(0.002)
U6_right			0.462			0.466*
			(0.107)			(0.071)
U7_right			-0.0267			0.685***
			(0.914)			(0.002)
U8_right			0.299			0.220
			(0.232)			(0.375)
U9_right			0.644***			0.588***
			(0.000)			(0.001)
Constant	-0.832	-1.549*	-3.115***	1.198	0.0763	-1.618
	(0.303)	(0.092)	(0.007)	(0.296)	(0.953)	(0.238)
Observations	952	925	925	952	925	925
Pseudo R^2	0.043	0.127	0.227	0.017	0.094	0.235
chi2	47.76	125.7	199.1	19.88	92.35	184.9

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.A.3 Republicans

Table 2.A.13: Tax support determinants

	(1) Tax Support	(2) Tax Support	(3) Tax Support	(4) Tax Support	(5) Tax Support	(6) Tax Support
treatment=1	-0.0948	-0.0333	-0.0745	-0.177	-0.0830	-0.0662
	(0.473)	(0.813)	(0.577)	(0.199)	(0.592)	(0.660)
republican=1	-1.896***	-0.428	-1.868***	-1.025***	-0.224	-0.296
	(0.000)	(0.104)	(0.000)	(0.000)	(0.474)	(0.339)
treatment=1 and republican=1	0.516*	0.522*	0.454	1.046***	0.936***	0.960***
	(0.066)	(0.082)	(0.114)	(0.001)	(0.005)	(0.004)
Age		0.00339			0.00948**	0.00788*
		(0.445)			(0.049)	(0.089)
$10,000 to $19,999		-0.0943			-0.110	-0.160
		(0.775)			(0.775)	(0.666)
$20,000 to $29,999		-0.334			-0.319	-0.234
		(0.270)			(0.382)	(0.510)
$30,000 to $39,999		0.139			0.181	0.159
		(0.640)			(0.609)	(0.641)
$40,000 to $49,999		0.392			0.541	0.484
		(0.224)			(0.151)	(0.185)
$50,000 to $59,999		0.375			0.401	0.509
		(0.280)			(0.304)	(0.190)
$60,000 to $69,999		-0.291			-0.288	-0.275
		(0.399)			(0.464)	(0.472)
$70,000 to $79,999		-0.152			-0.186	-0.148
		(0.679)			(0.661)	(0.719)
$80,000 to $89,999		0.0608			0.183	0.252
		(0.859)			(0.634)	(0.499)
$90,000 to $99,999		0.137			0.131	0.0868
		(0.716)			(0.754)	(0.834)
$100,000 to $149,999		0.202			0.402	0.357
		(0.516)			(0.253)	(0.301)
$150,000 or more		0.628*			0.763*	0.689*
		(0.072)			(0.053)	(0.074)
Female		-0.284**			-0.455***	-0.497***
		(0.023)			(0.001)	(0.000)
White		0.241			0.0928	0.126
		(0.107)			(0.583)	(0.443)
Political Scale		-0.405***			-0.221***	-0.220***
		(0.000)			(0.000)	(0.000)
High school graduate		1.171***			1.674**	1.777**
		(0.001)			(0.017)	(0.023)
Some college but no degree		1.081***			1.536**	1.679**
		(0.002)			(0.028)	(0.030)
Associate degree in college (2-year)		0.900**			1.218*	1.399*
		(0.017)			(0.091)	(0.076)
Bachelor's degree in college (4-year)		1.022***			1.308*	1.478*
		(0.002)			(0.057)	(0.053)
Master's degree		0.992***			1.131	1.366*
		(0.008)			(0.108)	(0.079)
Professional degree (JD, MD)		1.705***			1.917**	1.979**
		(0.001)			(0.012)	(0.017)
Doctoral degree		0.303			0.608	0.993
		(0.615)			(0.505)	(0.308)
In full or part time employment		-0.0476			-0.0218	-0.0300
		(0.736)			(0.892)	(0.846)
Student		0.380			0.0505	0.0483
		(0.164)			(0.865)	(0.868)
Democrat		0.508***			0.275	0.238
		(0.004)			(0.152)	(0.209)
religion_importance		-0.0579			-0.101	-0.122*
		(0.327)			(0.122)	(0.055)
U1_right			0.0466		-0.0191	0.0416
			(0.729)		(0.901)	(0.785)
U2_right			0.139		0.187	0.255*
			(0.299)		(0.227)	(0.094)
U3_right			0.335		-0.0954	-0.0962
			(0.202)		(0.775)	(0.772)
U4_right			-0.0810		-0.0735	-0.0561
			(0.515)		(0.604)	(0.686)
U5_right			-0.302**		-0.180	-0.228
			(0.036)		(0.253)	(0.141)
U6_right			-0.120		-0.102	-0.0591
			(0.535)		(0.671)	(0.797)
U7_right			0.199		-0.131	-0.152
			(0.275)		(0.533)	(0.464)
U8_right			0.0777		-0.0709	-0.0868
			(0.677)		(0.747)	(0.686)
U9_right			0.276**		0.256*	0.277*
			(0.039)		(0.094)	(0.063)
Worry about climate change				0.747***	0.666***	0.640***
				(0.000)	(0.000)	(0.000)
Global warming: hurting myself				0.0957	0.228*	0.227**
				(0.384)	(0.058)	(0.049)
Global warming: when does it hurt the US?				0.290***	0.228***	0.250***
				(0.000)	(0.002)	(0.000)
q1_graph_right					0.234	
					(0.414)	
q2_graph_right					0.326**	
					(0.032)	
q3_graph_right					-0.0117	
					(0.934)	
climate_U1right					0.106	
					(0.678)	
right_GHGs					-0.0415	
					(0.604)	
climate_U3right					-0.366***	
					(0.008)	
climate_U4right					0.249*	
					(0.090)	
climate_U5right					0.0814	
					(0.579)	
arousal					0.00157	
					(0.645)	
pleasure					0.00237	
					(0.512)	
Observations	959	943	959	914	882	898
Pseudo R^2	0.041	0.109	0.047	0.147	0.191	0.185
chi2	128.4	322.3	143.6	339.3	443.8	444.5

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.A.4 Study II

Table 2.A.14: Understanding 1 determinants

	(1)	(2)	(3)	(4)	(5)	(6)
	U1_right	U1_right	U1_right	U1_right	U1_right	U1_right
treatment=1	-0.126	-0.125	-0.150	-0.163	-0.153	-0.130
	(0.406)	(0.436)	(0.339)	(0.290)	(0.361)	(0.443)
republican=1	-0.598**	-0.339	-0.559**	-0.556**	-0.373	-0.398
	(0.011)	(0.245)	(0.020)	(0.023)	(0.223)	(0.197)
treatment=1 and republican=1	0.300	0.287	0.308	0.337	0.272	0.263
	(0.366)	(0.412)	(0.371)	(0.329)	(0.452)	(0.470)
Age		-0.00496			-0.00162	-0.00146
		(0.326)			(0.763)	(0.790)
$10,000 to $19,999		-0.127			0.00638	0.0874
		(0.740)			(0.987)	(0.829)
$20,000 to $29,999		0.210			0.186	0.268
		(0.551)			(0.606)	(0.461)
$30,000 to $39,999		0.273			0.315	0.386
		(0.445)			(0.380)	(0.288)
$40,000 to $49,999		0.282			0.390	0.481
		(0.447)			(0.311)	(0.218)
$50,000 to $59,999		0.0724			0.0698	0.119
		(0.849)			(0.860)	(0.765)
$60,000 to $69,999		-0.122			-0.173	-0.111
		(0.752)			(0.666)	(0.783)
$70,000 to $79,999		0.169			0.0466	0.114
		(0.684)			(0.911)	(0.784)
$80,000 to $89,999		0.0647			-0.0568	0.0409
		(0.876)			(0.891)	(0.922)
$90,000 to $99,999		-0.150			-0.124	-0.0271
		(0.727)			(0.780)	(0.952)
$100,000 to $149,999		0.401			0.392	0.454
		(0.266)			(0.291)	(0.224)
$150,000 or more		0.00338			0.0757	0.151
		(0.993)			(0.854)	(0.718)
Female		-0.396***			-0.251	-0.285*
		(0.006)			(0.101)	(0.067)
White		0.192			0.0671	0.0440
		(0.261)			(0.708)	(0.809)
Political Scale		-0.0257			-0.0202	-0.0233
		(0.639)			(0.719)	(0.685)
High school graduate		1.296			1.283*	1.323*
		(0.141)			(0.100)	(0.093)
Some college but no degree		1.384			1.263	1.310*
		(0.115)			(0.102)	(0.093)
Associate degree in college (2-year)		1.272			1.237	1.244
		(0.151)			(0.117)	(0.118)
Bachelor's degree in college (4-year)		1.503*			1.360*	1.341*
		(0.083)			(0.075)	(0.082)
Master's degree		1.346			1.159	1.133
		(0.128)			(0.140)	(0.152)
Professional degree (JD, MD)		2.550**			2.488**	2.467**
		(0.020)			(0.014)	(0.016)
Doctoral degree		0.373			0.108	0.172
		(0.739)			(0.922)	(0.876)
In full or part time employment		0.00505			0.0347	0.0931
		(0.975)			(0.839)	(0.589)
Student		0.244			0.130	0.117
		(0.481)			(0.715)	(0.745)
Democrat		0.124			0.0946	0.0924
		(0.528)			(0.640)	(0.654)
religion_importance		-0.166**			-0.0807	-0.0718
		(0.012)			(0.256)	(0.317)
q1_graph_right			0.272		0.237	0.210
			(0.298)		(0.403)	(0.470)
q2_graph_right			0.988***		0.925***	0.888***
			(0.000)		(0.000)	(0.000)
q3_graph_right			-0.380***		-0.328**	-0.349**
			(0.009)		(0.030)	(0.022)
climate_U1right				0.590**	0.426	0.417
				(0.028)	(0.134)	(0.155)
right_GHGs				0.282***	0.138	0.141
				(0.001)	(0.109)	(0.104)
climate_U3right				-0.107	-0.125	-0.0944
				(0.459)	(0.427)	(0.557)
climate_U4right				0.157	0.121	0.148
				(0.297)	(0.458)	(0.369)
climate_U5right				0.0806	0.00464	-0.0437
				(0.579)	(0.976)	(0.783)
arousal						-0.00339
						(0.306)
pleasure						-0.000771
						(0.829)
Constant	0.705***	-0.374	0.0493	-0.244	-1.680*	-1.489
	(0.000)	(0.692)	(0.861)	(0.374)	(0.067)	(0.114)
Observations	959	943	959	959	943	925
Pseudo R^2	0.006	0.042	0.052	0.028	0.086	0.086
chi2	8.233	44.96	62.28	33.22	93.89	90.47

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A.15: Understanding 2 determinants

	(1) U2_right	(2) U2_right	(3) U2_right	(4) U2_right	(5) U2_right	(6) U2_right
treatment=1	0.139	0.115	0.130	0.122	0.0997	0.0977
	(0.358)	(0.472)	(0.399)	(0.422)	(0.537)	(0.550)
republican=1	-0.518**	-0.0577	-0.494**	-0.475**	-0.0555	0.00998
	(0.027)	(0.840)	(0.043)	(0.049)	(0.851)	(0.973)
treatment=1 and republican=1	0.485	0.533	0.506	0.501	0.526	0.486
	(0.150)	(0.123)	(0.149)	(0.146)	(0.144)	(0.181)
Age		-0.0121**			-0.00968*	-0.00971*
		(0.016)			(0.062)	(0.064)
$10,000 to $19,999		-0.536			-0.505	-0.496
		(0.171)			(0.201)	(0.213)
$20,000 to $29,999		-0.177			-0.265	-0.307
		(0.621)			(0.481)	(0.416)
$30,000 to $39,999		-0.416			-0.436	-0.431
		(0.251)			(0.239)	(0.246)
$40,000 to $49,999		-0.0981			-0.0885	-0.0254
		(0.802)			(0.822)	(0.949)
$50,000 to $59,999		-0.290			-0.345	-0.385
		(0.462)			(0.395)	(0.344)
$60,000 to $69,999		-0.200			-0.294	-0.294
		(0.619)			(0.469)	(0.471)
$70,000 to $79,999		-0.286			-0.425	-0.409
		(0.498)			(0.323)	(0.338)
$80,000 to $89,999		-0.215			-0.371	-0.443
		(0.622)			(0.400)	(0.318)
$90,000 to $99,999		0.134			0.127	0.188
		(0.767)			(0.783)	(0.691)
$100,000 to $149,999		-0.150			-0.218	-0.188
		(0.690)			(0.575)	(0.632)
$150,000 or more		-0.213			-0.226	-0.0937
		(0.607)			(0.593)	(0.827)
Female		-0.0653			0.0744	0.0547
		(0.650)			(0.625)	(0.723)
White		-0.101			-0.224	-0.251
		(0.556)			(0.205)	(0.158)
Political Scale		0.0259			0.0285	0.0263
		(0.628)			(0.610)	(0.642)
High school graduate		-0.0562			-0.165	-0.119
		(0.949)			(0.840)	(0.885)
Some college but no degree		0.188			-0.00636	0.0478
		(0.830)			(0.994)	(0.953)
Associate degree in college (2-year)		-0.100			-0.227	-0.198
		(0.910)			(0.784)	(0.811)
Bachelor's degree in college (4-year)		0.177			-0.0213	0.0313
		(0.838)			(0.979)	(0.969)
Master's degree		0.291			0.0636	0.0763
		(0.741)			(0.938)	(0.926)
Professional degree (JD, MD)		0.177			0.0216	0.0444
		(0.857)			(0.982)	(0.962)
Doctoral degree		0.595			0.310	0.315
		(0.596)			(0.776)	(0.774)
In full or part time employment		-0.0349			-0.0230	-0.0674
		(0.829)			(0.891)	(0.691)
Student		0.266			0.144	0.0962
		(0.469)			(0.695)	(0.793)
Democrat		0.533***			0.523***	0.568***
		(0.006)			(0.008)	(0.005)
religion_importance		-0.188***			-0.128*	-0.130*
		(0.004)			(0.059)	(0.059)
q1_graph_right			0.729***		0.581**	0.580**
			(0.004)		(0.029)	(0.031)
q2_graph_right			0.802***		0.663***	0.663***
			(0.000)		(0.000)	(0.000)
q3_graph_right			-0.255*		-0.203	-0.227
			(0.074)		(0.174)	(0.134)
climate_U1right				0.230	0.131	0.0337
				(0.379)	(0.636)	(0.906)
right_GHGs				0.255***	0.181**	0.166*
				(0.002)	(0.035)	(0.054)
climate_U3right				-0.150	-0.224	-0.218
				(0.295)	(0.141)	(0.158)
climate_U4right				0.121	0.138	0.162
				(0.419)	(0.382)	(0.308)
climate_U5right				-0.0197	-0.143	-0.179
				(0.891)	(0.350)	(0.247)
arousal						0.00497
						(0.148)
pleasure						-0.00390
						(0.291)
Constant	0.540***	1.086	-0.504*	0.0113	0.0441	0.128
	(0.000)	(0.250)	(0.064)	(0.966)	(0.963)	(0.895)
Observations	959	943	959	959	943	925
Pseudo R^2	0.006	0.038	0.042	0.019	0.069	0.070
chi2	8.156	45.58	50.89	23.25	83.61	82.02

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A.16: Understanding 3 determinants

	(1)	(2)	(3)	(4)	(5)	(6)
	U3_score	U3_score	U3_score	U3_score	U3_score	U3_score
treatment=1	-0.00271	0.0271	-0.0171	-0.0128	0.00617	-0.0149
	(0.983)	(0.835)	(0.893)	(0.921)	(0.963)	(0.913)
republican=1	-0.625***	-0.301	-0.624***	-0.566***	-0.413	-0.395
	(0.001)	(0.226)	(0.003)	(0.006)	(0.109)	(0.125)
treatment=1 and republican=1	0.823***	0.756**	0.887***	0.831***	0.830***	0.863***
	(0.005)	(0.014)	(0.003)	(0.005)	(0.007)	(0.005)
Age		0.000798			0.00255	0.00188
		(0.853)			(0.564)	(0.678)
$10,000 to $19,999		-0.517			-0.403	-0.330
		(0.153)			(0.260)	(0.355)
$20,000 to $29,999		0.322			0.304	0.388
		(0.324)			(0.350)	(0.234)
$30,000 to $39,999		0.00587			-0.0305	0.0500
		(0.985)			(0.921)	(0.872)
$40,000 to $49,999		0.366			0.388	0.484
		(0.275)			(0.238)	(0.150)
$50,000 to $59,999		0.195			0.189	0.238
		(0.596)			(0.620)	(0.537)
$60,000 to $69,999		0.368			0.298	0.389
		(0.267)			(0.367)	(0.239)
$70,000 to $79,999		-0.00957			-0.103	-0.0164
		(0.979)			(0.776)	(0.964)
$80,000 to $89,999		0.422			0.331	0.410
		(0.212)			(0.315)	(0.219)
$90,000 to $99,999		0.330			0.320	0.388
		(0.386)			(0.411)	(0.321)
$100,000 to $149,999		0.460			0.393	0.460
		(0.150)			(0.218)	(0.148)
$150,000 or more		0.346			0.335	0.437
		(0.301)			(0.311)	(0.198)
Female		0.0679			0.212*	0.184
		(0.579)			(0.096)	(0.157)
White		0.112			-0.0138	-0.00413
		(0.436)			(0.928)	(0.979)
Political Scale		0.00237			0.0220	0.0134
		(0.961)			(0.650)	(0.789)
High school graduate		-0.370			-0.409	-0.385
		(0.514)			(0.312)	(0.338)
Some college but no degree		0.119			0.0111	0.0574
		(0.833)			(0.978)	(0.883)
Associate degree in college (2-year)		0.0729			0.0302	0.0459
		(0.900)			(0.943)	(0.913)
Bachelor's degree in college (4-year)		-0.0404			-0.146	-0.113
		(0.942)			(0.709)	(0.771)
Master's degree		-0.0590			-0.200	-0.196
		(0.918)			(0.622)	(0.626)
Professional degree (JD, MD)		0.290			0.105	0.0865
		(0.689)			(0.868)	(0.891)
Doctoral degree		-0.586			-0.801	-0.732
		(0.449)			(0.244)	(0.288)
In full or part time employment		-0.118			-0.120	-0.143
		(0.404)			(0.403)	(0.336)
Student		0.146			0.00874	-0.0623
		(0.635)			(0.977)	(0.838)
Democrat		0.407**			0.385**	0.377**
		(0.014)			(0.022)	(0.031)
religion_importance		-0.0765			-0.00315	0.00927
		(0.187)			(0.959)	(0.881)
q1_graph_right			0.851***		0.701***	0.683***
			(0.000)		(0.001)	(0.001)
q2_graph_right			0.547***		0.467***	0.439***
			(0.000)		(0.000)	(0.001)
q3_graph_right			-0.250**		-0.169	-0.150
			(0.038)		(0.190)	(0.251)
climate_U1right				0.620***	0.483***	0.475**
				(0.000)	(0.009)	(0.012)
right_GHGs				0.275***	0.211***	0.210***
				(0.000)	(0.004)	(0.005)
climate_U3right				0.0422	-0.0342	-0.0350
				(0.727)	(0.784)	(0.783)
climate_U4right				0.0281	-0.0183	-0.00347
				(0.818)	(0.885)	(0.978)
climate_U5right				0.106	0.0256	-0.00129
				(0.367)	(0.839)	(0.992)
arousal						-0.000551
						(0.852)
pleasure						-0.00296
						(0.365)
Observations	959	943	959	959	943	925
Pseudo R^2	0.004	0.017	0.015	0.014	0.031	0.031
chi2	12.74	57.42	47.58	62.16	125.7	122.1

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A.17: Understanding pca1 determinants

	(1)	(2)	(3)	(4)	(5)	(6)
	Scores for component 1	Scores for component 1	Scores for component 1	Scores for component 1	Scores for component 1	Scores for component 1
treatment=1	-0.0279	0.00273	-0.0404	-0.0626	-0.0276	-0.0268
	(0.812)	(0.982)	(0.724)	(0.589)	(0.811)	(0.820)
republican=1	-0.660***	-0.269	-0.621***	-0.623***	-0.330	-0.317
	(0.001)	(0.244)	(0.001)	(0.002)	(0.146)	(0.168)
treatment=1 and republican=1	0.629**	0.588**	0.626**	0.674**	0.604**	0.595**
	(0.023)	(0.036)	(0.022)	(0.014)	(0.026)	(0.031)
Age		-0.00215			0.0000538	-0.000166
		(0.579)			(0.989)	(0.966)
$10,000 to $19,999		-0.520			-0.434	-0.383
		(0.138)			(0.196)	(0.259)
$20,000 to $29,999		0.271			0.224	0.263
		(0.358)			(0.434)	(0.364)
$30,000 to $39,999		0.0896			0.0671	0.108
		(0.764)			(0.813)	(0.709)
$40,000 to $49,999		0.409			0.427	0.482*
		(0.168)			(0.130)	(0.096)
$50,000 to $59,999		0.135			0.134	0.148
		(0.682)			(0.681)	(0.653)
$60,000 to $69,999		0.371			0.288	0.323
		(0.243)			(0.348)	(0.300)
$70,000 to $79,999		0.0641			-0.0247	0.0207
		(0.848)			(0.940)	(0.950)
$80,000 to $89,999		0.338			0.221	0.259
		(0.298)			(0.472)	(0.409)
$90,000 to $99,999		0.197			0.181	0.238
		(0.585)			(0.609)	(0.509)
$100,000 to $149,999		0.395			0.320	0.369
		(0.182)			(0.264)	(0.206)
$150,000 or more		0.401			0.401	0.470
		(0.194)			(0.178)	(0.123)
Female		0.0204			0.144	0.116
		(0.855)			(0.194)	(0.304)
White		0.157			0.0438	0.0418
		(0.256)			(0.752)	(0.767)
Political Scale		-0.0280			-0.0159	-0.0211
		(0.529)			(0.712)	(0.631)
High school graduate		-0.140			-0.200	-0.176
		(0.805)			(0.622)	(0.667)
Some college but no degree		0.245			0.0879	0.134
		(0.661)			(0.823)	(0.736)
Associate degree in college (2-year)		0.00726			-0.0821	-0.0627
		(0.990)			(0.844)	(0.881)
Bachelor's degree in college (4-year)		0.0982			-0.0771	-0.0618
		(0.859)			(0.842)	(0.875)
Master's degree		0.104			-0.0793	-0.0762
		(0.855)			(0.845)	(0.852)
Professional degree (JD, MD)		0.330			0.140	0.144
		(0.603)			(0.783)	(0.779)
Doctoral degree		-0.389			-0.647	-0.605
		(0.617)			(0.353)	(0.389)
In full or part time employment		-0.0859			-0.0773	-0.0761
		(0.491)			(0.528)	(0.545)
Student		0.201			0.0643	0.0273
		(0.452)			(0.802)	(0.917)
Democrat		0.318**			0.279*	0.272*
		(0.038)			(0.058)	(0.076)
religion_importance		-0.108**			-0.0431	-0.0377
		(0.036)			(0.397)	(0.463)
q1_graph_right			0.721***		0.548***	0.529***
			(0.000)		(0.006)	(0.009)
q2_graph_right			0.679***		0.563***	0.538***
			(0.000)		(0.000)	(0.000)
q3_graph_right			-0.191*		-0.122	-0.120
			(0.072)		(0.258)	(0.275)
climate_U1right				0.571***	0.389*	0.360*
				(0.005)	(0.062)	(0.095)
right_GHGs				0.285***	0.202***	0.201***
				(0.000)	(0.002)	(0.002)
climate_U3right				0.0570	0.00637	0.0123
				(0.603)	(0.954)	(0.912)
climate_U4right				0.136	0.103	0.127
				(0.208)	(0.341)	(0.247)
climate_U5right				0.112	0.0245	-0.00581
				(0.301)	(0.823)	(0.958)
arousal						-0.000893
						(0.724)
pleasure						-0.000866
						(0.763)
Constant	0.0815	-0.234	-0.931***	-0.934***	-1.687***	-1.556***
	(0.315)	(0.704)	(0.000)	(0.000)	(0.002)	(0.006)
Observations	959	943	959	959	943	925
Adjusted R^2	0.0132	0.0678	0.0685	0.0591	0.1283	0.1230

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A.18: Understanding pca2 determinants

	(1)	(2)	(3)	(4)	(5)	(6)
	Scores for component 2	Scores for component 2	Scores for component 2	Scores for component 2	Scores for component 2	Scores for component 2
treatment=1	-0.0528	-0.0699	-0.0591	-0.0429	-0.0640	-0.0792
	(0.497)	(0.390)	(0.447)	(0.582)	(0.433)	(0.339)
republican=1	-0.0940	-0.151	-0.0779	-0.0601	-0.121	-0.109
	(0.485)	(0.353)	(0.563)	(0.655)	(0.449)	(0.503)
treatment=1 republican=1	0.357*	0.374*	0.354*	0.326*	0.335*	0.378*
	(0.062)	(0.056)	(0.062)	(0.087)	(0.082)	(0.051)
Age		0.000257			0.000299	-0.0000802
		(0.919)			(0.907)	(0.975)
$10,000 to $19,999		0.188			0.196	0.209
		(0.339)			(0.316)	(0.289)
$20,000 to $29,999		0.136			0.114	0.157
		(0.431)			(0.498)	(0.358)
$30,000 to $39,999		-0.0590			-0.0573	-0.0218
		(0.744)			(0.747)	(0.904)
$40,000 to $49,999		-0.0168			-0.000630	0.0449
		(0.926)			(0.997)	(0.807)
$50,000 to $59,999		0.0704			0.0850	0.119
		(0.718)			(0.658)	(0.543)
$60,000 to $69,999		-0.126			-0.122	-0.0706
		(0.503)			(0.511)	(0.704)
$70,000 to $79,999		-0.0260			-0.0458	-0.0208
		(0.899)			(0.819)	(0.918)
$80,000 to $89,999		0.217			0.222	0.254
		(0.302)			(0.281)	(0.232)
$90,000 to $99,999		0.232			0.235	0.235
		(0.277)			(0.275)	(0.277)
$100,000 to $149,999		0.0420			0.0470	0.0750
		(0.814)			(0.788)	(0.673)
$150,000 or more		-0.172			-0.183	-0.161
		(0.385)			(0.345)	(0.420)
Female		-0.195***			-0.166**	-0.165**
		(0.009)			(0.030)	(0.034)
White		-0.120			-0.110	-0.0941
		(0.168)			(0.208)	(0.288)
Political Scale		0.0490*			0.0487*	0.0438
		(0.078)			(0.079)	(0.119)
High school graduate		0.0432			-0.0111	-0.0107
		(0.928)			(0.981)	(0.982)
Some college but no degree		0.209			0.139	0.139
		(0.660)			(0.768)	(0.770)
Associate degree in college (2-year)		0.431			0.371	0.374
		(0.370)			(0.439)	(0.439)
Bachelor's degree in college (4-year)		0.233			0.175	0.192
		(0.623)			(0.709)	(0.685)
Master's degree		0.187			0.110	0.109
		(0.697)			(0.817)	(0.821)
Professional degree (JD, MD)		0.571			0.499	0.490
		(0.292)			(0.352)	(0.361)
Doctoral degree		0.225			0.206	0.241
		(0.665)			(0.693)	(0.648)
In full or part time employment		-0.0371			-0.0330	-0.0445
		(0.655)			(0.691)	(0.598)
Student		-0.0227			-0.0211	-0.0506
		(0.894)			(0.902)	(0.771)
Democrat		0.150			0.142	0.143
		(0.128)			(0.152)	(0.162)
religion_importance		-0.00615			0.00591	0.0162
		(0.859)			(0.868)	(0.653)
q1_graph_right			0.158		0.198	0.205
			(0.273)		(0.152)	(0.148)
q2_graph_right			0.0138		0.0134	0.0138
			(0.858)		(0.869)	(0.867)
q3_graph_right			-0.210***		-0.173**	-0.160**
			(0.004)		(0.024)	(0.039)
climate_U1right				0.00595	0.0285	0.0498
				(0.969)	(0.854)	(0.757)
right_GHGs				0.0502	0.0238	0.0242
				(0.214)	(0.571)	(0.568)
climate_U3right				-0.169**	-0.170**	-0.173**
				(0.021)	(0.022)	(0.021)
climate_U4right				-0.0983	-0.109	-0.111
				(0.199)	(0.156)	(0.154)
climate_U5right				-0.0203	-0.0240	-0.0249
				(0.781)	(0.748)	(0.743)
arousal						-0.00105
						(0.561)
pleasure						-0.00190
						(0.328)
Constant	0.0108	-0.240	-0.0167	0.0311	-0.257	-0.147
	(0.854)	(0.644)	(0.912)	(0.848)	(0.629)	(0.788)
Observations	959	943	959	959	943	925
Adjusted R^2	0.0051	0.0404	0.0147	0.0141	0.0560	0.0604

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A.19: Understanding pca3 determinants

	(1)	(2)	(3)	(4)	(5)	(6)
	Scores for component 3	Scores for component 3	Scores for component 3	Scores for component 3	Scores for component 3	Scores for component 3
treatment=1	0.00730	0.0137	0.0123	0.00416	0.0100	-0.0154
	(0.917)	(0.848)	(0.858)	(0.953)	(0.887)	(0.828)
republican=1	-0.0681	-0.208	-0.0945	-0.0839	-0.215	-0.224
	(0.586)	(0.164)	(0.449)	(0.507)	(0.153)	(0.142)
treatment=1 and republican=1	0.0785	0.0625	0.0833	0.0852	0.0838	0.107
	(0.655)	(0.722)	(0.638)	(0.629)	(0.638)	(0.553)
Age		0.00728***			0.00632***	0.00561**
		(0.002)			(0.009)	(0.021)
$10,000 to $19,999		-0.0922			-0.111	-0.125
		(0.576)			(0.503)	(0.451)
$20,000 to $29,999		-0.0229			-0.0145	0.00246
		(0.879)			(0.925)	(0.987)
$30,000 to $39,999		0.0956			0.0850	0.0976
		(0.517)			(0.571)	(0.518)
$40,000 to $49,999		0.0735			0.0452	0.0558
		(0.635)			(0.774)	(0.723)
$50,000 to $59,999		0.0305			0.0244	0.0486
		(0.856)			(0.886)	(0.778)
$60,000 to $69,999		0.112			0.118	0.124
		(0.486)			(0.474)	(0.458)
$70,000 to $79,999		0.0797			0.104	0.109
		(0.677)			(0.586)	(0.574)
$80,000 to $89,999		0.189			0.220	0.214
		(0.322)			(0.253)	(0.274)
$90,000 to $99,999		0.134			0.122	0.0819
		(0.464)			(0.494)	(0.638)
$100,000 to $149,999		0.0597			0.0573	0.0499
		(0.685)			(0.704)	(0.742)
$150,000 or more		0.211			0.193	0.182
		(0.209)			(0.261)	(0.299)
Female		0.236***			0.201***	0.211***
		(0.000)			(0.003)	(0.002)
White		0.109			0.126	0.141*
		(0.176)			(0.113)	(0.077)
Political Scale		-0.0215			-0.0214	-0.0205
		(0.365)			(0.369)	(0.392)
High school graduate		-0.348			-0.350	-0.386
		(0.346)			(0.340)	(0.295)
Some college but no degree		-0.434			-0.413	-0.434
		(0.235)			(0.256)	(0.234)
Associate degree in college (2-year)		-0.399			-0.406	-0.414
		(0.288)			(0.280)	(0.272)
Bachelor's degree in college (4-year)		-0.420			-0.397	-0.407
		(0.244)			(0.269)	(0.260)
Master's degree		-0.489			-0.457	-0.457
		(0.184)			(0.214)	(0.217)
Professional degree (JD, MD)		-0.564			-0.567	-0.574
		(0.211)			(0.205)	(0.202)
Doctoral degree		-0.291			-0.271	-0.252
		(0.569)			(0.596)	(0.628)
In full or part time employment		-0.0234			-0.0278	-0.0337
		(0.759)			(0.716)	(0.662)
Student		-0.151			-0.121	-0.139
		(0.307)			(0.416)	(0.356)
Democrat		-0.202**			-0.192**	-0.193**
		(0.018)			(0.024)	(0.026)
religion_importance		0.0436			0.0234	0.0273
		(0.166)			(0.474)	(0.408)
q1_graph_right			-0.0509		-0.0190	-0.0374
			(0.698)		(0.890)	(0.787)
q2_graph_right			-0.297***		-0.247***	-0.225***
			(0.000)		(0.001)	(0.004)
q3_graph_right			0.154**		0.116*	0.124*
			(0.017)		(0.079)	(0.061)
climate_U1right				0.0664	0.0495	0.111
				(0.654)	(0.741)	(0.458)
right_GHGs				-0.0723*	-0.0316	-0.0236
				(0.061)	(0.435)	(0.559)
climate_U3right				0.0132	0.0188	0.0256
				(0.844)	(0.784)	(0.713)
climate_U4right				0.0482	0.0487	0.0364
				(0.490)	(0.491)	(0.609)
climate_U5right				-0.0253	0.00113	0.00753
				(0.705)	(0.987)	(0.912)
arousal						-0.000301
						(0.853)
pleasure						-0.00147
						(0.398)
Constant	0.00183	-0.00712	0.159	0.0305	0.135	0.194
	(0.971)	(0.986)	(0.271)	(0.835)	(0.749)	(0.647)
Observations	959	943	959	959	943	925
Adjusted R^2	0.0005	0.0502	0.0267	0.0048	0.0673	0.0674

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A.20: Summary statistics for key demographics of respondents in Study II. The samples for this experiment were recruited on CloudResearch to match the demographics of representative samples of the U.S. population. We note that despite leaving the survey open for over a month older respondents (above 60 years) and Native Americans are under-represented in our final survey.

	Control			**Group Treatment**			**Total**		
	No.	%	%	No.	%	%	No.	%	%
Gender									
Other/Prefer not to declare	108	18.8	18.8	105	18.4	18.4	213	18.6	18.6
Female	249	43.4	62.2	240	42.1	60.5	489	42.7	61.4
Male	217	37.8	100.0	225	39.5	100.0	442	38.6	100.0
Total	574	100.0		570	100.0		1,144	100.0	
Age									
18-25 years old	66	11.5	11.5	62	10.9	10.9	128	11.2	11.2
26-35 years old	108	18.8	30.3	101	17.7	28.6	209	18.3	29.5
36-45 years old	78	13.6	43.9	102	17.9	46.5	180	15.7	45.2
46-55 years old	81	14.1	58.0	74	13.0	59.5	155	13.5	58.7
56-65 years old	93	16.2	74.2	90	15.8	75.3	183	16.0	74.7
66-75 years old	44	7.7	81.9	47	8.2	83.5	91	8.0	82.7
>75 years old	104	18.1	100.0	94	16.5	100.0	198	17.3	100.0
Total	574	100.0		570	100.0		1,144	100.0	
income									
$10,000 to $19,999	32	6.7	6.7	42	8.7	8.7	74	7.7	7.7
$100,000 to $149,999	66	13.8	20.5	61	12.7	21.4	127	13.2	20.9
$150,000 or more	26	5.4	25.9	32	6.7	28.1	58	6.0	27.0
$20,000 to $29,999	41	8.6	34.4	48	10.0	38.0	89	9.3	36.2
$30,000 to $39,999	64	13.4	47.8	51	10.6	48.6	115	12.0	48.2
$40,000 to $49,999	55	11.5	59.3	44	9.1	57.8	99	10.3	58.5
$50,000 to $59,999	45	9.4	68.7	51	10.6	68.4	96	10.0	68.5
$60,000 to $69,999	42	8.8	77.5	35	7.3	75.7	77	8.0	76.6
$70,000 to $79,999	40	8.4	85.8	34	7.1	82.7	74	7.7	84.3
$80,000 to $89,999	26	5.4	91.2	24	5.0	87.7	50	5.2	89.5
$90,000 to $99,999	19	4.0	95.2	30	6.2	94.0	49	5.1	94.6
Less than $10,000	23	4.8	100.0	29	6.0	100.0	52	5.4	100.0
Total	479	100.0		481	100.0		960	100.0	
education									
Associate degree in college (2-year)	59	12.3	12.3	68	14.0	14.0	127	13.2	13.2
Bachelor's degree in college (4-year)	174	36.2	48.5	168	34.7	48.8	342	35.5	48.7
Doctoral degree	12	2.5	51.0	8	1.7	50.4	20	2.1	50.7
High school graduate (high school diploma or equivalent including GED)	45	9.4	60.4	62	12.8	63.2	107	11.1	61.8
Less than high school degree	1	0.2	60.6	2	0.4	63.6	3	0.3	62.1
Master's degree	68	14.2	74.8	77	15.9	79.5	145	15.0	77.2
Professional degree (JD, MD)	9	1.9	76.7	9	1.9	81.4	18	1.9	79.0
Some college but no degree	112	23.3	100.0	90	18.6	100.0	202	21.0	100.0
Total	480	100.0		484	100.0		964	100.0	
Political Orientation									
Republican	125	21.8	21.8	137	24.0	24.0	262	22.9	22.9
Democrat	246	42.9	64.6	224	39.3	63.3	470	41.1	64.0
No strong preference	203	35.4	100.0	209	36.7	100.0	412	36.0	100.0
Total	574	100.0		570	100.0		1,144	100.0	
In full or part time employment									
	335	58.4	100.0	334	58.6	100.0	669	58.5	100.0
Total	574	100.0		570	100.0		1,144	100.0	
Student									
	22	3.8	100.0	17	3.0	100.0	39	3.4	100.0
Total	574	100.0		570	100.0		1,144	100.0	
White									
	389	67.8	100.0	397	69.6	100.0	786	68.7	100.0
Total	574	100.0		570	100.0		1,144	100.0	

Table 2.A.21: Preferred subsidy

	(1) Subsidy	(2) Subsidy	(3) Subsidy	(4) Subsidy	(5) Subsidy	(6) Subsidy
treatment	1.617	1.263	1.366	1.588	1.753	1.701
	(0.231)	(0.319)	(0.275)	(0.219)	(0.176)	(0.176)
Age	-0.0862**			-0.131***	-0.147***	-0.142***
	(0.050)			(0.001)	(0.001)	(0.002)
$10,000 to $19,999	-3.595			-1.956	-2.502	-2.821
	(0.386)			(0.614)	(0.508)	(0.434)
$20,000 to $29,999	-4.351			-1.907	-1.825	-1.153
	(0.286)			(0.624)	(0.630)	(0.753)
$30,000 to $39,999	-3.999			-1.801	-2.889	-2.975
	(0.286)			(0.606)	(0.412)	(0.373)
$40,000 to $49,999	-1.095			0.660	0.272	0.448
	(0.784)			(0.860)	(0.941)	(0.898)
$50,000 to $59,999	-1.731			-0.567	-1.195	-1.270
	(0.673)			(0.882)	(0.757)	(0.734)
$60,000 to $69,999	-0.227			1.480	-0.265	-1.178
	(0.956)			(0.701)	(0.944)	(0.743)
$70,000 to $79,999	-6.052			-4.292	-6.178	-7.205*
	(0.129)			(0.254)	(0.113)	(0.060)
$80,000 to $89,999	-8.041**			-6.298*	-7.329*	-7.483**
	(0.039)			(0.093)	(0.056)	(0.047)
$90,000 to $99,999	-7.711*			-5.077	-5.210	-5.251
	(0.050)			(0.164)	(0.157)	(0.147)
$100,000 to $149,999	-6.067			-4.556	-5.170	-4.536
	(0.112)			(0.197)	(0.146)	(0.185)
$150,000 or more	-1.860			-1.452	-3.519	-3.264
	(0.657)			(0.706)	(0.381)	(0.406)
Female	4.718***			4.424***	4.571***	3.512**
	(0.001)			(0.001)	(0.001)	(0.011)
High school graduate	-8.215			-5.761	-4.925	-1.582
	(0.527)			(0.634)	(0.691)	(0.921)
Some college but no degree	-14.08			-10.46	-9.532	-4.747
	(0.275)			(0.385)	(0.437)	(0.767)
Associate degree in college (2-year)	-8.043			-5.261	-3.370	-0.272
	(0.534)			(0.664)	(0.785)	(0.986)
Bachelor's degree in college (4-year)	-14.09			-8.818	-7.888	-3.652
	(0.273)			(0.462)	(0.518)	(0.819)
Master's degree	-12.17			-6.066	-5.797	-1.322
	(0.346)			(0.616)	(0.639)	(0.934)
Professional degree (JD, MD)	-18.71			-10.44	-8.432	-4.324
	(0.159)			(0.401)	(0.503)	(0.790)
Doctoral degree	-12.20			-7.327	-6.621	-0.684
	(0.359)			(0.554)	(0.599)	(0.967)
familiar-IPCC	-1.347			-0.836		
	(0.223)			(0.379)		
Worry about climate change		-2.108**		-1.711*	-0.219	-0.257
		(0.010)		(0.052)	(0.822)	(0.791)
Global warming: hurting myself		2.360**		1.280	1.102	1.123
		(0.026)		(0.222)	(0.289)	(0.275)
Global warming: when does it hurt the US?		-2.594***		-2.556***	-2.247***	-2.134***
		(0.000)		(0.000)	(0.000)	(0.001)
U1_right			-11.10***	-10.19***	-9.584***	-6.963***
			(0.000)	(0.000)	(0.000)	(0.001)
U2_medhigh_right			0.408	0.555	0.443	0.453
			(0.921)	(0.805)	(0.839)	(0.827)
U2_lowvlow_right			0	-1.032	-1.554	-1.088
			(.)	(0.652)	(0.480)	(0.605)
U2_highvhigh_right			-4.112	-2.952	-1.876	-1.154
			(0.185)	(0.157)	(0.358)	(0.560)
U2_lowhigh_right			-0.444	-0.171	-0.664	0.212
			(0.891)	(0.934)	(0.743)	(0.913)
U2_score			0.574	0	0	0
			(0.800)	(.)	(.)	(.)
U3_right			-4.429***	-3.670***	-2.936**	-1.955
			(0.000)	(0.005)	(0.024)	(0.133)
White					-2.421	-1.191
					(0.174)	(0.514)
Political Scale					2.405***	2.290***
					(0.000)	(0.000)
In full or part time employment					1.748	1.658
					(0.288)	(0.322)
Student					-1.537	-0.0143
					(0.626)	(0.996)
Republican					-3.084	-3.308
					(0.159)	(0.129)
Democrat					0.925	0.156
					(0.601)	(0.928)
religion_importance					0.875	0.422
					(0.151)	(0.488)
q1_graph_right						-8.932***
						(0.005)
q2_graph_right						-3.353**
						(0.032)
q3_graph_right						0.493
						(0.699)
climate_U1right						-8.589***
						(0.002)
right_GHGs						-1.979**
						(0.045)
climate_U3right						-1.036
						(0.419)
climate_U4right						0.247
						(0.862)
climate_U5right						-0.445
						(0.739)
arousal						0.0455
						(0.111)
pleasure						0.0210
						(0.529)
Constant	39.65***	33.04***	34.02***	59.41***	45.71***	55.94***
	(0.003)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Observations	949	1020	1046	928	911	906
Adjusted R^2	0.0591	0.0683	0.0609	0.1798	0.2153	0.2636

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A.22: Support for tax

	(1) Tax Support	(2) Tax Support	(3) Tax Support	(4) Tax Support	(5) Tax Support	(6) Tax Support
Tax Support						
treatment	0.0880	0.145	-0.00202	0.199	0.233*	0.225*
	(0.458)	(0.213)	(0.985)	(0.119)	(0.076)	(0.096)
Age	-0.0119***			0.000450	0.00687	0.00782*
	(0.003)			(0.911)	(0.138)	(0.091)
\$10,000 to \$19,999	0.244			0.201	0.251	0.230
	(0.440)			(0.563)	(0.486)	(0.534)
\$20,000 to \$29,999	0.254			-0.231	-0.0745	-0.102
	(0.453)			(0.524)	(0.838)	(0.782)
\$30,000 to \$39,999	-0.120			-0.376	-0.307	-0.333
	(0.667)			(0.245)	(0.361)	(0.337)
\$40,000 to \$49,999	0.0802			-0.162	-0.0503	-0.0363
	(0.771)			(0.615)	(0.879)	(0.915)
\$50,000 to \$59,999	0.00587			-0.149	-0.0773	-0.0923
	(0.984)			(0.658)	(0.825)	(0.798)
\$60,000 to \$69,999	-0.0483			-0.373	-0.139	-0.139
	(0.866)			(0.269)	(0.699)	(0.712)
\$70,000 to \$79,999	0.129			0.0872	0.396	0.369
	(0.658)			(0.799)	(0.244)	(0.297)
\$80,000 to \$89,999	-0.193			-0.226	-0.157	-0.150
	(0.590)			(0.545)	(0.684)	(0.710)
\$90,000 to \$99,999	-0.105			-0.0344	0.0118	-0.0173
	(0.779)			(0.927)	(0.976)	(0.966)
\$100,000 to \$149,999	-0.0628			-0.232	-0.172	-0.163
	(0.826)			(0.464)	(0.602)	(0.633)
\$150,000 or more	-0.257			-0.239	0.139	0.0969
	(0.471)			(0.518)	(0.722)	(0.813)
Female	-0.103			-0.309**	-0.336**	-0.330**
	(0.385)			(0.016)	(0.012)	(0.017)
High school graduate	1.108			1.296	0.939	0.180
	(0.399)			(0.667)	(0.699)	(0.955)
Some college but no degree	1.726			1.950	1.497	0.747
	(0.188)			(0.516)	(0.536)	(0.813)
Associate degree in college (2-year)	1.329			1.697	1.233	0.435
	(0.312)			(0.572)	(0.611)	(0.891)
Bachelor's degree in college (4-year)	1.867			1.993	1.605	0.812
	(0.154)			(0.506)	(0.507)	(0.798)
Master's degree	2.083			2.148	1.569	0.768
	(0.113)			(0.475)	(0.518)	(0.808)
Professional degree (JD, MD)	2.506*			2.463	1.894	1.104
	(0.078)			(0.416)	(0.442)	(0.730)
Doctoral degree	1.910			1.934	1.849	0.952
	(0.177)			(0.522)	(0.447)	(0.765)
familiar-IPCC	0.248***			0.188**		
	(0.003)			(0.016)		
Worry about climate change		0.878***		0.899***	0.683***	0.694***
		(0.000)		(0.000)	(0.000)	(0.000)
Global warming: hurting myself		0.207**		0.250**	0.306***	0.304**
		(0.046)		(0.026)	(0.010)	(0.011)
Global warming: when does it hurt the US?		0.190***		0.206***	0.154**	0.138**
		(0.001)		(0.001)	(0.014)	(0.030)
U1_right			0.424***	0.150	0.0365	0.0410
			(0.002)	(0.417)	(0.852)	(0.842)
U2_medhigh_right			-0.184	-0.0522	-0.121	-0.128
			(0.213)	(0.791)	(0.548)	(0.529)
U2_lowvlow_right			0.0342	0.0672	0.103	0.125
			(0.830)	(0.753)	(0.634)	(0.567)
U2_highvhigh_right			0.311**	0.419**	0.449**	0.450**
			(0.038)	(0.018)	(0.016)	(0.016)
U2_lowhigh_right			-0.166	-0.291*	-0.338*	-0.360*
			(0.243)	(0.095)	(0.062)	(0.051)
U2_score			0	0	0	0
			(.)	(.)	(.)	(.)
U3_right			0.233**	0.168	0.125	0.125
			(0.041)	(0.181)	(0.329)	(0.342)
White					0.440**	0.415**
					(0.018)	(0.031)
Political Scale					-0.218***	-0.225***
					(0.000)	(0.000)
In full or part time employment					0.171	0.142
					(0.293)	(0.391)
Student					0.435	0.374
					(0.275)	(0.356)
Republican					-0.454**	-0.516**
					(0.041)	(0.020)
Democrat					0.242	0.216
					(0.193)	(0.249)
religion_importance					0.0252	0.0276
					(0.688)	(0.659)
q1_graph_right						-0.142
						(0.591)
q2_graph_right						0.198
						(0.213)
q3_graph_right						-0.0394
						(0.775)
climate_U1right						-0.466*
						(0.061)
right_GHGs						0.0933
						(0.282)
climate_U3right						0.0153
						(0.912)
climate_U4right						0.0533
						(0.712)
climate_U5right						0.0645
						(0.650)
arousal						0.00556*
						(0.059)
pleasure						-0.00182
						(0.566)
Observations	970	1043	1069	949	930	924
Pseudo R^2	0.018	0.163	0.006	0.189	0.214	0.217
chi2	53.98	376.2	25.49	383.9	456.0	475.0

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A.23: Worry about global warming

	(1) Worry about climate change	(2) Worry about climate change	(3) Worry about climate change	(4) Worry about climate change	(5) Worry about climate change
Worry about climate change					
treatment	-0.131	-0.210*	-0.135	-0.0651	-0.0334
	(0.278)	(0.059)	(0.266)	(0.624)	(0.806)
Age	-0.0185***		-0.0194***	-0.00429	-0.00510
	(0.000)		(0.000)	(0.369)	(0.303)
$10,000 to $19,999	-0.0359		-0.129	-0.0224	-0.0389
	(0.913)		(0.700)	(0.956)	(0.927)
$20,000 to $29,999	0.594*		0.533	0.546	0.518
	(0.088)		(0.129)	(0.188)	(0.233)
$30,000 to $39,999	0.176		0.0581	0.139	0.119
	(0.565)		(0.852)	(0.720)	(0.769)
$40,000 to $49,999	0.165		0.0759	0.134	0.0862
	(0.604)		(0.815)	(0.744)	(0.840)
$50,000 to $59,999	0.216		0.128	0.122	0.0271
	(0.527)		(0.710)	(0.771)	(0.951)
$60,000 to $69,999	0.332		0.233	0.478	0.414
	(0.304)		(0.475)	(0.250)	(0.336)
$70,000 to $79,999	0.148		0.0244	0.387	0.337
	(0.665)		(0.944)	(0.353)	(0.434)
$80,000 to $89,999	0.0331		-0.0728	0.0474	0.0416
	(0.927)		(0.843)	(0.914)	(0.926)
$90,000 to $99,999	-0.143		-0.267	-0.352	-0.422
	(0.699)		(0.477)	(0.447)	(0.380)
$100,000 to $149,999	0.139		0.0127	0.0712	-0.00450
	(0.664)		(0.969)	(0.860)	(0.991)
$150,000 or more	-0.139		-0.274	0.322	0.354
	(0.697)		(0.449)	(0.462)	(0.440)
Female	0.243**		0.276**	0.304**	0.354**
	(0.048)		(0.025)	(0.028)	(0.015)
High school graduate	0.175		0.0731	-0.455	0.718
	(0.833)		(0.927)	(0.795)	(0.823)
Some college but no degree	0.595		0.485	-0.255	0.967
	(0.470)		(0.539)	(0.883)	(0.763)
Associate degree in college (2-year)	0.296		0.205	-0.551	0.681
	(0.721)		(0.796)	(0.751)	(0.832)
Bachelor's degree in college (4-year)	0.676		0.556	-0.278	0.967
	(0.407)		(0.476)	(0.872)	(0.764)
Master's degree	0.822		0.737	-0.282	0.968
	(0.322)		(0.355)	(0.871)	(0.764)
Professional degree (JD, MD)	1.221		1.051	-0.129	1.140
	(0.215)		(0.277)	(0.944)	(0.727)
Doctoral degree	1.005		0.949	0.981	2.242
	(0.285)		(0.304)	(0.582)	(0.491)
familiar-IPCC	0.148		0.147*		
	(0.101)		(0.097)		
U1_right		0.372**	0.437***	0.331	0.264
		(0.011)	(0.009)	(0.111)	(0.214)
U2_medhigh_right		-0.0779	-0.131	-0.188	-0.173
		(0.646)	(0.464)	(0.352)	(0.383)
U2_lowvlow_right		-0.0980	-0.125	-0.0956	-0.112
		(0.576)	(0.506)	(0.649)	(0.591)
U2_highvhigh_right		0.0640	0.146	-0.00449	0.00880
		(0.706)	(0.428)	(0.982)	(0.965)
U2_lowhigh_right		-0.0422	-0.195	-0.0868	-0.134
		(0.797)	(0.271)	(0.654)	(0.506)
U2_score		0	0	0	0
		(.)	(.)	(.)	(.)
U3_right		0.150	0.165	0.00585	0.0194
		(0.198)	(0.189)	(0.965)	(0.889)
White				0.211	0.178
				(0.279)	(0.380)
Political Scale				-0.391***	-0.402***
				(0.000)	(0.000)
In full or part time employment				0.0996	0.0582
				(0.556)	(0.735)
Student				0.208	0.146
				(0.559)	(0.688)
Republican				-0.764***	-0.740***
				(0.000)	(0.001)
Democrat				0.801***	0.734***
				(0.000)	(0.000)
religion_importance				-0.181***	-0.188***
				(0.005)	(0.005)
q1_graph_right					0.0648
					(0.788)
q2_graph_right					-0.0408
					(0.802)
q3_graph_right					0.0733
					(0.602)
climate_U1right					0.108
					(0.627)
right_GHGs					0.0889
					(0.320)
climate_U3right					0.316**
					(0.027)
climate_U4right					0.453***
					(0.004)
climate_U5right					0.239
					(0.101)
arousal					0.000428
					(0.892)
pleasure					0.00342
					(0.322)
Observations	974	1074	974	955	949
Pseudo R^2	0.018	0.004	0.022	0.175	0.185
chi2	49.04	13.65	63.84	441.0	474.8

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A.24: Perceived harm from global warming

	(1) GW hurts me	(2) GW hurts me	(3) GW hurts me	(4) GW hurts me	(5) GW hurts me
GW hurts me					
treatment	-0.0352	-0.101	-0.0239	-0.00567	0.0232
	(0.773)	(0.368)	(0.845)	(0.964)	(0.858)
Age	-0.0232***		-0.0233***	-0.0159***	-0.0163***
	(0.000)		(0.000)	(0.001)	(0.001)
$10,000 to $19,999	-0.189		-0.237	-0.237	-0.288
	(0.609)		(0.529)	(0.548)	(0.466)
$20,000 to $29,999	0.508		0.427	0.339	0.308
	(0.177)		(0.260)	(0.388)	(0.449)
$30,000 to $39,999	-0.0323		-0.115	-0.133	-0.201
	(0.924)		(0.738)	(0.725)	(0.605)
$40,000 to $49,999	0.00783		-0.0219	-0.155	-0.218
	(0.982)		(0.950)	(0.683)	(0.574)
$50,000 to $59,999	-0.386		-0.438	-0.604	-0.753*
	(0.283)		(0.221)	(0.112)	(0.054)
$60,000 to $69,999	0.0140		-0.0550	-0.0684	-0.148
	(0.968)		(0.875)	(0.862)	(0.719)
$70,000 to $79,999	-0.164		-0.281	-0.122	-0.209
	(0.651)		(0.445)	(0.757)	(0.604)
$80,000 to $89,999	-0.275		-0.352	-0.409	-0.446
	(0.447)		(0.334)	(0.319)	(0.284)
$90,000 to $99,999	-0.269		-0.370	-0.494	-0.592
	(0.489)		(0.350)	(0.252)	(0.183)
$100,000 to $149,999	-0.177		-0.258	-0.319	-0.410
	(0.605)		(0.459)	(0.398)	(0.298)
$150,000 or more	-0.595		-0.714*	-0.432	-0.457
	(0.114)		(0.060)	(0.281)	(0.265)
Female	0.364***		0.403***	0.361***	0.451***
	(0.003)		(0.001)	(0.005)	(0.001)
High school graduate	1.097		1.027	1.219	0.683
	(0.144)		(0.193)	(0.245)	(0.500)
Some college but no degree	1.421*		1.356*	1.419	0.922
	(0.057)		(0.084)	(0.171)	(0.361)
Associate degree in college (2-year)	1.156		1.095	1.200	0.728
	(0.122)		(0.163)	(0.249)	(0.472)
Bachelor's degree in college (4-year)	1.447**		1.381*	1.348	0.854
	(0.050)		(0.077)	(0.191)	(0.398)
Master's degree	1.630**		1.603**	1.476	0.976
	(0.029)		(0.042)	(0.156)	(0.336)
Professional degree (JD, MD)	1.658*		1.557*	1.392	0.943
	(0.066)		(0.096)	(0.226)	(0.403)
Doctoral degree	1.147		1.156	1.549	1.023
	(0.152)		(0.173)	(0.155)	(0.344)
familiar-IPCC	0.180**		0.182**		
	(0.041)		(0.040)		
U1_right		0.284*	0.268	0.152	0.212
		(0.077)	(0.136)	(0.423)	(0.287)
U2_medhigh_right		0.0182	0.0206	-0.0462	-0.0807
		(0.915)	(0.907)	(0.796)	(0.650)
U2_lowvlow_right		-0.295*	-0.385**	-0.350*	-0.350*
		(0.098)	(0.045)	(0.068)	(0.068)
U2_highvhigh_right		-0.0733	-0.00895	-0.204	-0.143
		(0.664)	(0.961)	(0.285)	(0.471)
U2_lowhigh_right		0.0793	-0.0326	0.116	0.0891
		(0.632)	(0.855)	(0.536)	(0.645)
U2_score		0	0	0	0
		(.)	(.)	(.)	(.)
U3_right		0.0909	0.145	0.0801	0.104
		(0.443)	(0.258)	(0.544)	(0.452)
White				-0.201	-0.282
				(0.226)	(0.102)
Political Scale				-0.278***	-0.279***
				(0.000)	(0.000)
In full or part time employment				-0.0599	-0.0605
				(0.717)	(0.726)
Student				-0.559*	-0.576*
				(0.080)	(0.068)
Republican				-0.505**	-0.510**
				(0.015)	(0.016)
Democrat				0.672***	0.634***
				(0.000)	(0.000)
religion_importance				-0.0577	-0.0799
				(0.333)	(0.202)
q1_graph_right					-0.471*
					(0.078)
q2_graph_right					-0.0393
					(0.801)
q3_graph_right					0.0531
					(0.697)
climate_U1right					0.194
					(0.403)
right_GHGs					0.170**
					(0.048)
climate_U3right					0.356***
					(0.009)
climate_U4right					0.337**
					(0.020)
climate_U5right					-0.112
					(0.414)
arousal					-0.000748
					(0.815)
pleasure					0.00669*
					(0.065)
Observations	953	1048	953	934	928
Pseudo R^2	0.029	0.003	0.033	0.127	0.138
chi2	75.16	8.771	91.65	283.0	311.5

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A.25: Speed at which global warming hurts the US

	(1) GW hurts USA	(2) GW hurts USA	(3) GW hurts USA	(4) GW hurts USA	(5) GW hurts USA
GW hurts USA					
treatment	-0.146	-0.191*	-0.144	-0.0996	-0.0948
	(0.243)	(0.099)	(0.254)	(0.463)	(0.498)
Age	-0.0128***		-0.0138***	-0.00388	-0.00442
	(0.001)		(0.001)	(0.435)	(0.393)
$10,000 to $19,999	0.0602		-0.0315	0.111	0.124
	(0.862)		(0.930)	(0.791)	(0.769)
$20,000 to $29,999	0.349		0.285	0.319	0.333
	(0.300)		(0.407)	(0.425)	(0.424)
$30,000 to $39,999	0.331		0.190	0.297	0.262
	(0.289)		(0.559)	(0.438)	(0.508)
$40,000 to $49,999	0.0989		0.00516	-0.0427	-0.0874
	(0.758)		(0.988)	(0.914)	(0.830)
$50,000 to $59,999	0.0672		-0.0246	0.0581	0.0405
	(0.841)		(0.943)	(0.883)	(0.920)
$60,000 to $69,999	0.171		0.0621	0.227	0.229
	(0.604)		(0.854)	(0.568)	(0.575)
$70,000 to $79,999	-0.112		-0.259	-0.0937	-0.111
	(0.734)		(0.449)	(0.808)	(0.780)
$80,000 to $89,999	-0.0878		-0.215	-0.0691	-0.0930
	(0.817)		(0.581)	(0.872)	(0.830)
$90,000 to $99,999	0.0917		-0.0496	0.0141	0.0275
	(0.822)		(0.907)	(0.976)	(0.955)
$100,000 to $149,999	-0.115		-0.263	-0.201	-0.271
	(0.723)		(0.439)	(0.596)	(0.487)
$150,000 or more	-0.423		-0.602	-0.0562	-0.0786
	(0.265)		(0.128)	(0.893)	(0.855)
Female	0.211*		0.251**	0.233	0.322**
	(0.093)		(0.049)	(0.103)	(0.035)
High school graduate	-1.306		-1.509*	-1.782	-0.802
	(0.140)		(0.061)	(0.294)	(0.479)
Some college but no degree	-0.917		-1.119	-1.509	-0.524
	(0.302)		(0.166)	(0.373)	(0.647)
Associate degree in college (2-year)	-1.230		-1.405*	-1.880	-0.850
	(0.167)		(0.082)	(0.267)	(0.457)
Bachelor's degree in college (4-year)	-0.709		-0.916	-1.386	-0.378
	(0.421)		(0.253)	(0.411)	(0.740)
Master's degree	-0.564		-0.719	-1.300	-0.305
	(0.528)		(0.377)	(0.444)	(0.790)
Professional degree (JD, MD)	-0.397		-0.637	-1.578	-0.590
	(0.690)		(0.492)	(0.367)	(0.631)
Doctoral degree	-0.898		-0.975	-0.663	0.149
	(0.354)		(0.275)	(0.698)	(0.900)
familiar-IPCC	0.0917		0.0820		
	(0.340)		(0.385)		
U1_right		0.495***	0.473***	0.426**	0.363*
		(0.001)	(0.009)	(0.043)	(0.100)
U2_medhigh_right		-0.0981	-0.0849	-0.139	-0.140
		(0.581)	(0.657)	(0.501)	(0.509)
U2_lowvlow_right		-0.193	-0.239	-0.212	-0.248
		(0.288)	(0.230)	(0.318)	(0.269)
U2_highvhigh_right		0.204	0.241	0.0612	0.0722
		(0.234)	(0.204)	(0.775)	(0.735)
U2_lowhigh_right		-0.0942	-0.185	-0.0476	-0.130
		(0.568)	(0.311)	(0.816)	(0.525)
U2_score		0	0	0	0
		(.)	(.)	(.)	(.)
U3_right		0.0631	0.0830	-0.104	-0.135
		(0.617)	(0.540)	(0.472)	(0.367)
White				-0.139	-0.242
				(0.481)	(0.233)
Political Scale				-0.357***	-0.368***
				(0.000)	(0.000)
In full or part time employment				-0.193	-0.278
				(0.304)	(0.149)
Student				-0.505	-0.683*
				(0.159)	(0.078)
Republican				-0.813***	-0.835***
				(0.000)	(0.000)
Democrat				0.361*	0.283
				(0.052)	(0.142)
religion_importance				-0.140**	-0.151**
				(0.027)	(0.023)
q1_graph_right					-0.441*
					(0.090)
q2_graph_right					0.349**
					(0.027)
q3_graph_right					0.177
					(0.237)
climate_U1right					0.209
					(0.394)
right_GHGs					0.205**
					(0.026)
climate_U3right					0.123
					(0.421)
climate_U4right					0.345**
					(0.035)
climate_U5right					0.328**
					(0.032)
arousal					0.00353
					(0.310)
pleasure					0.00150
					(0.701)
Observations	974	1074	974	955	949
Pseudo R^2	0.013	0.005	0.018	0.129	0.142
chi2	35.06	17.46	46.69	307.8	349.4

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A.26: Understanding determinants per question

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	U1_right	U1_right	U1_right	U2_score	U2_score	U2_score	U3_right	U3_right	U3_right
treatment	0.126	0.182	0.0882	0.0745	0.0915	0.0443	-0.00270	-0.0254	-0.0811
	(0.539)	(0.385)	(0.692)	(0.530)	(0.447)	(0.723)	(0.984)	(0.850)	(0.562)
Age	0.0111*	0.0146*	0.0177**	-0.00242	-0.00194	-0.000108	-0.00217	0.00230	0.00413
	(0.087)	(0.058)	(0.034)	(0.529)	(0.660)	(0.981)	(0.612)	(0.638)	(0.415)
$10,000 to $19,999	0.924**	1.099**	1.147**	0.0264	0.00719	-0.0639	0.343	0.391	0.470
	(0.046)	(0.029)	(0.030)	(0.939)	(0.984)	(0.857)	(0.366)	(0.328)	(0.237)
$20,000 to $29,999	0.570	0.629	0.794	-0.329	-0.328	-0.436	0.438	0.341	0.352
	(0.162)	(0.148)	(0.104)	(0.310)	(0.321)	(0.189)	(0.230)	(0.368)	(0.348)
$30,000 to $39,999	1.242***	1.556***	1.575***	-0.343	-0.334	-0.496	-0.191	-0.247	-0.219
	(0.004)	(0.001)	(0.001)	(0.249)	(0.283)	(0.105)	(0.591)	(0.508)	(0.547)
$40,000 to $49,999	1.020**	1.380***	1.469***	0.0990	0.130	0.0131	0.129	0.0709	0.0941
	(0.020)	(0.005)	(0.009)	(0.754)	(0.689)	(0.967)	(0.723)	(0.853)	(0.802)
$50,000 to $59,999	0.491	0.708	0.963**	-0.278	-0.217	-0.269	0.151	0.145	0.232
	(0.234)	(0.102)	(0.048)	(0.374)	(0.504)	(0.398)	(0.681)	(0.707)	(0.537)
$60,000 to $69,999	1.127**	1.568***	1.768***	-0.201	-0.166	-0.232	-0.0192	-0.0388	0.0568
	(0.021)	(0.003)	(0.002)	(0.540)	(0.623)	(0.500)	(0.960)	(0.923)	(0.885)
$70,000 to $79,999	1.479***	1.889***	2.003***	-0.377	-0.323	-0.358	0.233	0.209	0.267
	(0.006)	(0.001)	(0.001)	(0.259)	(0.351)	(0.316)	(0.542)	(0.603)	(0.500)
$80,000 to $89,999	1.245**	1.466**	1.556**	0.0140	0.0350	-0.0586	0.0950	0.101	0.130
	(0.034)	(0.016)	(0.015)	(0.970)	(0.927)	(0.878)	(0.820)	(0.817)	(0.764)
$90,000 to $99,999	1.291**	1.598**	1.684**	-0.107	-0.132	-0.277	0.384	0.273	0.282
	(0.040)	(0.012)	(0.011)	(0.765)	(0.723)	(0.476)	(0.363)	(0.538)	(0.527)
$100,000 to $149,999	1.243***	1.547***	1.625***	-0.248	-0.241	-0.432	0.232	0.142	0.150
	(0.007)	(0.002)	(0.003)	(0.423)	(0.455)	(0.176)	(0.519)	(0.705)	(0.683)
$150,000 or more	1.846***	2.190***	2.243***	-0.316	-0.306	-0.483	-0.119	-0.0843	-0.156
	(0.006)	(0.002)	(0.003)	(0.380)	(0.414)	(0.195)	(0.773)	(0.848)	(0.720)
Female	-0.431**	-0.420**	-0.307	-0.0320	-0.0533	0.0227	-0.379***	-0.335**	-0.257*
	(0.035)	(0.045)	(0.180)	(0.792)	(0.669)	(0.860)	(0.004)	(0.015)	(0.075)
High school graduate	2.218**	2.220*	0.722	13.24***	13.45***	13.71***	0.463	0.390	-0.546
	(0.038)	(0.082)	(0.381)	(0.000)	(0.000)	(0.000)	(0.707)	(0.727)	(0.690)
Some college but no degree	2.761***	2.756**	1.132	13.22***	13.38***	13.47***	0.460	0.353	-0.741
	(0.010)	(0.031)	(0.152)	(0.000)	(0.000)	(0.000)	(0.707)	(0.751)	(0.588)
Associate degree in college (2-year)	2.226**	2.113*	0.510	13.26***	13.49***	13.68***	0.250	0.163	-0.827
	(0.037)	(0.097)	(0.523)	(0.000)	(0.000)	(0.000)	(0.839)	(0.884)	(0.546)
Bachelor's degree in college (4-year)	2.911***	2.905**	1.273	13.41***	13.66***	13.77***	0.575	0.514	-0.545
	(0.006)	(0.022)	(0.103)	(0.000)	(0.000)	(0.000)	(0.638)	(0.642)	(0.690)
Master's degree	2.684**	2.739**	0.983	14.00***	14.24***	14.31***	0.864	0.794	-0.334
	(0.014)	(0.035)	(0.222)	(0.000)	(0.000)	(0.000)	(0.482)	(0.477)	(0.808)
Professional degree (JD, MD)	3.318**	3.155*	1.299	14.33***	14.59***	14.64***	1.799	1.695	0.571
	(0.031)	(0.066)	(0.368)	(0.000)	(0.000)	(0.000)	(0.179)	(0.169)	(0.696)
Doctoral degree	1.968	1.856	0	13.86***	14.15***	14.18***	0.824	0.811	-0.397
	(0.110)	(0.188)	(.)	(0.000)	(0.000)	(0.000)	(0.525)	(0.494)	(0.784)
familiarIPCC	-0.0400			0.0721			0.144		
	(0.776)			(0.373)			(0.103)		
White		0.247	0.235		0.0943	-0.0282		0.322*	0.223
		(0.348)	(0.409)		(0.587)	(0.876)		(0.079)	(0.237)
Political Scale		-0.101	-0.0582		-0.0264	-0.0182		-0.143***	-0.143***
		(0.214)	(0.429)		(0.539)	(0.685)		(0.003)	(0.005)
In full or part time employment		-0.697***	-0.793***		-0.0338	0.0567		0.193	0.217
		(0.010)	(0.009)		(0.825)	(0.714)		(0.252)	(0.209)
Student		-0.432	-0.798		0.332	0.243		0.339	0.250
		(0.425)	(0.178)		(0.361)	(0.501)		(0.389)	(0.533)
Republican		0.443	0.204		-0.138	-0.142		-0.0166	0.0322
		(0.196)	(0.555)		(0.461)	(0.464)		(0.938)	(0.885)
Democrat		0.218	0.246		-0.177	-0.122		-0.418**	-0.360*
		(0.438)	(0.415)		(0.293)	(0.486)		(0.024)	(0.058)
religion_importance		-0.259***	-0.156		0.0738	0.122**		-0.0284	0.00489
		(0.006)	(0.128)		(0.191)	(0.042)		(0.648)	(0.940)
q1_graph_right			1.034***			0.363*			0.772**
			(0.004)			(0.081)			(0.012)
q2_graph_right			0.796***			0.709***			0.593***
			(0.001)			(0.000)			(0.000)
q3_graph_right			0.0786			-0.284**			-0.161
			(0.732)			(0.034)			(0.258)
climate_U1right			0.205			0.167			0.345
			(0.536)			(0.430)			(0.179)
right_GHGs			0.210			0.00575			0.0709
			(0.181)			(0.942)			(0.445)
climate_U3right			0.267			0.145			-0.142
			(0.242)			(0.279)			(0.337)
climate_U4right			0.0697			-0.0155			-0.110
			(0.788)			(0.912)			(0.474)
climate_U5right			0.437*			0.0980			0.0375
			(0.083)			(0.460)			(0.800)
arousal			0.00823			-0.000607			-0.000434
			(0.142)			(0.819)			(0.891)
pleasure			-0.0216***			-0.00581**			-0.000731
			(0.001)			(0.042)			(0.833)
Constant	-1.936*	-1.545	-1.618				-0.604	-0.327	-0.735
	(0.099)	(0.286)	(0.173)				(0.636)	(0.786)	(0.628)
Observations	974	955	947	974	955	949	974	955	949
Pseudo R^2	0.063	0.099	0.174	0.015	0.017	0.036	0.026	0.036	0.061
chi2	47.61	69.65	109.7	532.3	610.3	.	31.81	45.21	75.07

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A.27: Understanding determinants overall

	(1) U_tot	(2) U_tot	(3) U_tot	(4) U_tot	(5) Scores for component 1	(6) Scores for component 1	(7) Scores for component 1	(8) Scores for component 1
treatment	0.0601	0.0875	0.103	0.0529	0.0613	0.0716	0.0885	0.0319
	(0.557)	(0.452)	(0.385)	(0.666)	(0.577)	(0.542)	(0.457)	(0.787)
Age		-0.00215	-0.000607	0.00120		-0.00185	-0.00159	0.000449
		(0.562)	(0.886)	(0.785)		(0.620)	(0.710)	(0.916)
$10,000 to $19,999		0.215	0.237	0.269		0.213	0.197	0.135
		(0.563)	(0.535)	(0.488)		(0.545)	(0.583)	(0.694)
$20,000 to $29,999		-0.131	-0.153	-0.134		-0.117	-0.108	-0.241
		(0.714)	(0.676)	(0.718)		(0.728)	(0.752)	(0.458)
$30,000 to $39,999		-0.192	-0.168	-0.207		-0.245	-0.192	-0.313
		(0.572)	(0.635)	(0.552)		(0.429)	(0.548)	(0.300)
$40,000 to $49,999		0.232	0.281	0.271		0.216	0.257	0.127
		(0.516)	(0.444)	(0.450)		(0.514)	(0.444)	(0.688)
$50,000 to $59,999		-0.162	-0.0955	-0.0188		-0.209	-0.118	-0.146
		(0.654)	(0.799)	(0.960)		(0.530)	(0.728)	(0.647)
$60,000 to $69,999		-0.00957	0.0438	0.0936		-0.0918	-0.0302	-0.0448
		(0.979)	(0.905)	(0.806)		(0.785)	(0.930)	(0.895)
$70,000 to $79,999		-0.132	-0.0605	0.0488		-0.226	-0.135	-0.175
		(0.714)	(0.872)	(0.902)		(0.508)	(0.700)	(0.607)
$80,000 to $89,999		0.171	0.204	0.231		0.126	0.193	0.0699
		(0.657)	(0.610)	(0.576)		(0.738)	(0.621)	(0.851)
$90,000 to $99,999		0.119	0.103	0.0305		0.0531	0.0835	-0.0541
		(0.749)	(0.790)	(0.940)		(0.886)	(0.828)	(0.886)
$100,000 to $149,999		-0.0297	-0.0200	-0.0921		-0.0867	-0.0455	-0.235
		(0.931)	(0.956)	(0.799)		(0.787)	(0.890)	(0.458)
$150,000 or more		-0.145	-0.0985	-0.183		-0.205	-0.149	-0.315
		(0.705)	(0.806)	(0.651)		(0.575)	(0.691)	(0.382)
Female		-0.150	-0.161	-0.0658		-0.0772	-0.103	0.00566
		(0.208)	(0.191)	(0.606)		(0.520)	(0.402)	(0.963)
High school graduate		2.678***	2.656***	2.710***		1.749***	1.693***	1.244***
		(0.000)	(0.000)	(0.007)		(0.000)	(0.000)	(0.000)
Some college but no degree		2.733***	2.645***	2.494**		1.822***	1.699***	1.072***
		(0.000)	(0.000)	(0.013)		(0.000)	(0.000)	(0.000)
Associate degree in college (2-year)		2.699***	2.669***	2.660***		1.703***	1.649***	1.145***
		(0.000)	(0.000)	(0.007)		(0.000)	(0.000)	(0.000)
Bachelor's degree in college (4-year)		2.930***	2.939***	2.833***		1.992***	1.972***	1.357***
		(0.000)	(0.000)	(0.004)		(0.000)	(0.000)	(0.000)
Master's degree		3.501***	3.497***	3.340***		2.568***	2.532***	1.850***
		(0.000)	(0.000)	(0.001)		(0.000)	(0.000)	(0.000)
Professional degree (JD, MD)		4.017***	3.988***	3.826***		2.941***	2.891***	2.195***
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Doctoral degree		3.408***	3.436***	3.190***		2.380***	2.387***	1.639***
		(0.000)	(0.000)	(0.002)		(0.000)	(0.000)	(0.000)
familiar-IPCC		0.0898				0.0796		
		(0.239)				(0.312)		
White			0.156	0.0208			0.0780	-0.0589
			(0.362)	(0.906)			(0.648)	(0.726)
Political Scale			-0.0616	-0.0573			-0.0612	-0.0440
			(0.143)	(0.185)			(0.143)	(0.275)
In full or part time employment			-0.0167	0.0652			-0.121	-0.0496
			(0.912)	(0.668)			(0.417)	(0.733)
Student			0.373	0.257			0.282	0.157
			(0.299)	(0.476)			(0.444)	(0.656)
Republican			-0.0909	-0.0673			-0.0961	-0.0962
			(0.630)	(0.733)			(0.610)	(0.599)
Democrat			-0.230	-0.158			-0.203	-0.104
			(0.161)	(0.352)			(0.229)	(0.530)
religion_importance			0.0472	0.107*			0.0693	0.117**
			(0.386)	(0.064)			(0.206)	(0.032)
q1_graph_right				0.600**				0.603***
				(0.010)				(0.001)
q2_graph_right				0.833***				0.757***
				(0.000)				(0.000)
q3_graph_right				-0.245*				-0.338***
				(0.067)				(0.008)
climate_U1right				0.285				0.220
				(0.215)				(0.250)
right_GHGs				0.0268				0.0382
				(0.730)				(0.612)
climate_U3right				0.162				0.109
				(0.204)				(0.380)
climate_U4right				-0.0510				-0.000103
				(0.707)				(0.999)
climate_U5right				0.122				0.0961
				(0.343)				(0.440)
arousal				0.000155				-0.000625
				(0.954)				(0.807)
pleasure				-0.00720**				-0.00699**
				(0.011)				(0.012)
Constant					-0.0306	-1.619***	-1.349***	-1.644***
					(0.691)	(0.000)	(0.008)	(0.005)
Observations	1169	974	955	949	1169	974	955	949
(Pseudo) R^2	0.000	0.012	0.014	0.032	0.0003	0.0406	0.0474	0.1183
chi2	0.345	58.81	64.02	125.1				

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A.28: Understanding determinants overall

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Scores for component 2	Scores for component 2	Scores for component 2	Scores for component 2	Scores for component 3	Scores for component 3	Scores for component 3	Scores for component 3
treatment	0.00233	-0.0338	-0.0411	-0.0570	0.0399	0.0326	0.0331	0.0206
	(0.971)	(0.642)	(0.570)	(0.423)	(0.497)	(0.617)	(0.617)	(0.759)
Age		0.00172	0.00386	0.00476*		0.000802	0.00129	0.00149
		(0.453)	(0.143)	(0.067)		(0.706)	(0.606)	(0.554)
\$10,000 to \$19,999		0.0491	0.126	0.116		0.392**	0.401**	0.462**
		(0.821)	(0.568)	(0.587)		(0.046)	(0.047)	(0.023)
\$20,000 to \$29,999		0.148	0.171	0.179		0.372**	0.314*	0.363*
		(0.488)	(0.424)	(0.385)		(0.038)	(0.090)	(0.052)
\$30,000 to \$39,999		0.133	0.182	0.211		0.307*	0.300	0.340*
		(0.515)	(0.384)	(0.294)		(0.083)	(0.102)	(0.065)
\$40,000 to \$49,999		0.134	0.211	0.216		0.239	0.218	0.262
		(0.532)	(0.334)	(0.306)		(0.179)	(0.241)	(0.161)
\$50,000 to \$59,999		-0.0143	0.0671	0.133		0.376**	0.337*	0.368*
		(0.947)	(0.759)	(0.523)		(0.044)	(0.080)	(0.057)
\$60,000 to \$69,999		0.112	0.238	0.278		0.320*	0.299	0.333*
		(0.615)	(0.295)	(0.205)		(0.099)	(0.136)	(0.099)
\$70,000 to \$79,999		0.366*	0.450**	0.462**		0.362*	0.337*	0.375*
		(0.093)	(0.042)	(0.031)		(0.056)	(0.086)	(0.057)
\$80,000 to \$89,999		0.0875	0.131	0.171		0.343	0.356*	0.390*
		(0.725)	(0.606)	(0.496)		(0.103)	(0.097)	(0.066)
\$90,000 to \$99,999		0.182	0.186	0.212		0.439**	0.443**	0.471**
		(0.441)	(0.447)	(0.366)		(0.041)	(0.045)	(0.033)
\$100,000 to \$149,999		0.162	0.206	0.247		0.415**	0.405**	0.437**
		(0.443)	(0.339)	(0.236)		(0.021)	(0.029)	(0.018)
\$150,000 or more		0.392	0.480*	0.471*		0.200	0.219	0.245
		(0.101)	(0.054)	(0.055)		(0.318)	(0.293)	(0.238)
Female		-0.262***	-0.227***	-0.197***		-0.0476	-0.0385	-0.0306
		(0.000)	(0.002)	(0.007)		(0.467)	(0.567)	(0.659)
High school graduate		0.381	0.354	0.389		0.363	0.344	0.681
		(0.167)	(0.223)	(0.201)		(0.326)	(0.358)	(0.119)
Some college but no degree		0.370	0.373	0.331		0.513	0.470	0.798*
		(0.171)	(0.190)	(0.276)		(0.156)	(0.197)	(0.064)
Associate degree in college (2-year)		0.329	0.297	0.305		0.353	0.300	0.622
		(0.236)	(0.309)	(0.324)		(0.335)	(0.416)	(0.153)
Bachelor's degree in college (4-year)		0.450*	0.459	0.430		0.469	0.404	0.733*
		(0.091)	(0.103)	(0.156)		(0.191)	(0.263)	(0.089)
Master's degree		0.372	0.412	0.342		0.424	0.340	0.661
		(0.186)	(0.162)	(0.284)		(0.248)	(0.360)	(0.133)
Professional degree (JD, MD)		1.103***	1.037***	0.962***		0.228	0.145	0.450
		(0.001)	(0.003)	(0.008)		(0.555)	(0.711)	(0.326)
Doctoral degree		0.161	0.155	0.00761		0.482	0.418	0.729
		(0.687)	(0.702)	(0.986)		(0.275)	(0.346)	(0.152)
familiar-IPCC		0.0485				-0.00940		
		(0.324)				(0.826)		
White			0.225**	0.179*			0.0137	0.0256
			(0.016)	(0.069)			(0.872)	(0.767)
Political Scale			-0.0229	-0.0199			-0.0468*	-0.0428*
			(0.377)	(0.431)			(0.059)	(0.080)
In full or part time employment			-0.0528	-0.0736			0.0201	0.0163
			(0.571)	(0.430)			(0.805)	(0.841)
Student			0.239	0.181			-0.220	-0.227
			(0.229)	(0.361)			(0.201)	(0.191)
Republican			0.126	0.113			0.0255	0.00277
			(0.284)	(0.330)			(0.814)	(0.979)
Democrat			-0.00406	0.0115			-0.0622	-0.0741
			(0.967)	(0.907)			(0.494)	(0.428)
religion_importance			-0.108***	-0.0827**			-0.00674	-0.00388
			(0.001)	(0.015)			(0.825)	(0.901)
q1_graph_right				0.352**				0.178
				(0.022)				(0.204)
q2_graph_right				0.298***				-0.0233
				(0.000)				(0.761)
q3_graph_right				0.0659				0.0218
				(0.374)				(0.752)
climate_U1right				-0.0514				0.207
				(0.685)				(0.125)
right_GHGs				0.0767				0.00305
				(0.119)				(0.945)
climate_U3right				-0.0788				0.0294
				(0.311)				(0.678)
climate_U4right				-0.0187				-0.0299
				(0.817)				(0.685)
climate_U5right				0.125				-0.0397
				(0.112)				(0.585)
arousal				0.000127				0.00145
				(0.941)				(0.328)
pleasure				-0.00122				-0.00139
				(0.511)				(0.401)
Constant	-0.00116	-0.376	-0.487	-1.104**	-0.0199	-0.663*	-0.455	-1.178**
	(0.980)	(0.269)	(0.206)	(0.015)	(0.626)	(0.099)	(0.295)	(0.029)
Observations	1169	974	955	949	1169	974	955	949
Adjusted R^2	0.0000	0.0379	0.0629	0.0956	0.0004	0.0161	0.0234	0.0345

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A.29: Time in policy and perception determinants

	(1)	(2)	(3)	(4)	(5)	(6)
	time_policy	time_policy	time_policy	time_perception	time_perception	time_perception
treatment	-2.798	-4.894	-7.374	1.271	1.397	1.913
	(0.675)	(0.465)	(0.269)	(0.529)	(0.512)	(0.421)
Age	1.652***	1.643***	1.624***	0.137**	0.138**	0.126**
	(0.000)	(0.000)	(0.000)	(0.013)	(0.014)	(0.038)
\$10,000 to \$19,999	48.19**	53.09***	53.76***	-1.608	-2.283	-2.388
	(0.012)	(0.006)	(0.005)	(0.613)	(0.477)	(0.477)
\$20,000 to \$29,999	45.43***	49.35***	45.31***	1.060	1.280	1.704
	(0.003)	(0.001)	(0.003)	(0.773)	(0.735)	(0.657)
\$30,000 to \$39,999	60.56***	67.07***	63.55***	-1.364	-1.144	-0.635
	(0.000)	(0.000)	(0.000)	(0.671)	(0.737)	(0.854)
\$40,000 to \$49,999	44.61***	48.20***	46.05***	-2.189	-1.730	-1.272
	(0.003)	(0.001)	(0.001)	(0.491)	(0.609)	(0.713)
\$50,000 to \$59,999	25.05*	34.21**	31.49**	-2.207	-2.126	-2.610
	(0.073)	(0.018)	(0.024)	(0.533)	(0.575)	(0.503)
\$60,000 to \$69,999	55.12***	61.01***	62.60***	-1.824	-2.268	-1.632
	(0.003)	(0.001)	(0.001)	(0.569)	(0.516)	(0.638)
\$70,000 to \$79,999	37.49**	44.62***	40.68***	9.926	10.18	10.37
	(0.024)	(0.008)	(0.009)	(0.300)	(0.300)	(0.304)
\$80,000 to \$89,999	37.15**	50.73***	43.02***	0.902	1.789	2.550
	(0.013)	(0.001)	(0.003)	(0.882)	(0.775)	(0.680)
\$90,000 to \$99,999	33.32**	43.88***	37.94**	-4.803	-3.680	-3.499
	(0.034)	(0.005)	(0.014)	(0.143)	(0.289)	(0.324)
\$100,000 to \$149,999	50.28***	59.04***	50.27***	-1.918	-1.066	-1.201
	(0.000)	(0.000)	(0.000)	(0.589)	(0.770)	(0.746)
\$150,000 or more	37.33*	48.67**	41.36*	-4.032	-3.740	-3.655
	(0.082)	(0.028)	(0.052)	(0.253)	(0.313)	(0.334)
Female	7.736	6.356	11.65*	2.514	2.419	2.210
	(0.258)	(0.340)	(0.087)	(0.190)	(0.229)	(0.315)
High school graduate	47.74**	43.24*	7.117	-12.55	-11.38	-20.19
	(0.022)	(0.074)	(0.762)	(0.289)	(0.387)	(0.213)
Some college but no degree	46.08**	43.49*	-1.531	-13.41	-12.20	-20.82
	(0.022)	(0.069)	(0.946)	(0.257)	(0.353)	(0.200)
Associate degree in college (2-year)	37.95*	33.18	-2.845	-12.72	-11.81	-20.38
	(0.073)	(0.176)	(0.905)	(0.284)	(0.371)	(0.210)
Bachelor's degree in college (4-year)	34.21	33.05	-8.662	-11.86	-11.14	-19.25
	(0.100)	(0.170)	(0.711)	(0.325)	(0.406)	(0.246)
Master's degree	33.26	35.84	-7.578	-9.754	-9.244	-17.25
	(0.128)	(0.151)	(0.745)	(0.420)	(0.487)	(0.302)
Professional degree (JD, MD)	51.75*	45.49	1.594	-17.46	-16.70	-24.28
	(0.098)	(0.177)	(0.961)	(0.144)	(0.208)	(0.141)
Doctoral degree	10.93	13.83	-34.64	-14.28	-13.13	-20.02
	(0.695)	(0.641)	(0.249)	(0.238)	(0.330)	(0.232)
familiar-IPCC	1.797			-0.456		
	(0.703)			(0.586)		
White		-28.62**	-33.54***		-6.645	-6.311
		(0.022)	(0.007)		(0.106)	(0.126)
Political Scale		-4.006	-3.064		0.218	0.163
		(0.106)	(0.206)		(0.776)	(0.834)
In full or part time employment		-21.29***	-17.09**		-0.906	-0.981
		(0.010)	(0.031)		(0.629)	(0.595)
Student		12.33	5.614		-2.938	-1.991
		(0.511)	(0.760)		(0.249)	(0.437)
Republican		-7.345	-4.909		-0.0140	0.187
		(0.523)	(0.664)		(0.996)	(0.953)
Democrat		-24.57**	-19.81**		0.234	0.288
		(0.015)	(0.042)		(0.918)	(0.899)
religion_importance		1.275	2.445		-0.0190	-0.164
		(0.692)	(0.458)		(0.981)	(0.844)
q1_graph_right			28.54*			2.868
			(0.074)			(0.195)
q2_graph_right			17.38**			-2.513
			(0.034)			(0.325)
q3_graph_right			-24.47***			1.645
			(0.001)			(0.254)
climate_U1right			34.63***			2.247
			(0.001)			(0.396)
right_GHGs			3.267			-0.0128
			(0.387)			(0.994)
climate_U3right			-1.660			0.114
			(0.792)			(0.947)
climate_U4right			3.445			-0.256
			(0.666)			(0.902)
climate_U5right			2.509			-3.850**
			(0.696)			(0.029)
arousal			0.0290			0.00512
			(0.834)			(0.805)
pleasure			-0.0993			0.0458
			(0.537)			(0.194)
Constant	-3.508	57.03*	38.63	27.42**	31.34**	34.40*
	(0.896)	(0.075)	(0.317)	(0.031)	(0.031)	(0.053)
Observations	974	955	949	974	955	949
R^2	0.088	0.111	0.146	0.025	0.033	0.043

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A.30: Time for understanding and duration determinants

	(1) time_understanding	(2) time_understanding	(3) time_understanding	(4) Time: full survey	(5) Time: full survey	(6) Time: full survey
treatment	-2.905	-4.482	-7.124	-525.6	-662.6	-673.8
	(0.729)	(0.594)	(0.387)	(0.611)	(0.543)	(0.517)
Age	3.237***	3.170***	3.214***	12.75	24.55	31.27
	(0.000)	(0.000)	(0.000)	(0.667)	(0.275)	(0.210)
$10,000 to $19,999	17.48	23.31	24.89	91.98	-6.633	1.957
	(0.473)	(0.350)	(0.299)	(0.811)	(0.991)	(0.997)
$20,000 to $29,999	30.72	37.54	37.99	615.2	289.8	397.8
	(0.197)	(0.130)	(0.107)	(0.320)	(0.631)	(0.523)
$30,000 to $39,999	39.03*	47.75**	46.93**	1015.8	597.4	598.8
	(0.076)	(0.041)	(0.037)	(0.166)	(0.511)	(0.531)
$40,000 to $49,999	26.08	33.44	32.08	267.5	-184.6	-434.3
	(0.242)	(0.153)	(0.159)	(0.536)	(0.662)	(0.399)
$50,000 to $59,999	26.28	41.56*	40.63*	3091.8	2962.6	3010.3
	(0.273)	(0.097)	(0.091)	(0.140)	(0.168)	(0.161)
$60,000 to $69,999	30.90	40.32	44.00*	5872.9	5311.3	5231.5
	(0.196)	(0.113)	(0.078)	(0.246)	(0.284)	(0.281)
$70,000 to $79,999	10.69	16.58	16.16	171.4	-337.6	-203.4
	(0.651)	(0.504)	(0.491)	(0.750)	(0.572)	(0.789)
$80,000 to $89,999	-4.089	11.93	9.524	235.6	77.04	336.0
	(0.859)	(0.629)	(0.680)	(0.745)	(0.914)	(0.736)
$90,000 to $99,999	24.87	36.45	30.64	284.6	11.46	-40.41
	(0.347)	(0.181)	(0.256)	(0.744)	(0.988)	(0.956)
$100,000 to $149,999	18.02	27.87	19.27	437.4	-40.50	103.0
	(0.392)	(0.213)	(0.382)	(0.628)	(0.955)	(0.913)
$150,000 or more	11.60	19.69	10.26	7046.7	6870.9	6952.9
	(0.630)	(0.447)	(0.686)	(0.281)	(0.283)	(0.282)
Female	-0.177	-0.0253	11.76	442.6	706.3	587.5
	(0.983)	(0.998)	(0.152)	(0.684)	(0.583)	(0.704)
High school graduate	-58.88	-64.07	-15.26	1220.1	805.6	-24.80
	(0.406)	(0.328)	(0.701)	(0.421)	(0.648)	(0.988)
Some college but no degree	-31.92	-35.58	-1.260	2730.0	2699.4	2029.9
	(0.653)	(0.589)	(0.975)	(0.279)	(0.296)	(0.448)
Associate degree in college (2-year)	-63.04	-64.40	-16.10	1566.3	1470.0	891.0
	(0.376)	(0.328)	(0.684)	(0.378)	(0.465)	(0.596)
Bachelor's degree in college (4-year)	-55.53	-52.68	-12.94	1388.2	1351.4	591.6
	(0.434)	(0.422)	(0.748)	(0.346)	(0.496)	(0.782)
Master's degree	-55.00	-46.25	-13.00	1507.7	1587.2	646.7
	(0.440)	(0.485)	(0.750)	(0.453)	(0.430)	(0.519)
Professional degree (JD, MD)	-33.48	-35.23	-1.585	-1032.9	-1148.5	-2156.3
	(0.656)	(0.618)	(0.974)	(0.710)	(0.637)	(0.297)
Doctoral degree	-50.74	-42.49	-17.51	-705.1	-632.8	-492.8
	(0.504)	(0.546)	(0.715)	(0.740)	(0.774)	(0.755)
familiar-IPCC	5.029			158.1		
	(0.384)			(0.759)		
White		-25.87**	-35.54***		-712.1	-1134.3
		(0.038)	(0.004)		(0.629)	(0.432)
Political Scale		-2.022	-0.885		-605.9	-670.0
		(0.519)	(0.773)		(0.280)	(0.260)
In full or part time employment		-26.55**	-24.45**		859.6	807.1
		(0.017)	(0.020)		(0.201)	(0.250)
Student		15.54	3.298		-505.7	-233.1
		(0.398)	(0.854)		(0.690)	(0.887)
Republican		-20.44	-17.59		-410.5	-6.134
		(0.152)	(0.201)		(0.763)	(0.996)
Democrat		-44.15***	-37.91***		-3604.1	-3628.4
		(0.000)	(0.001)		(0.233)	(0.258)
religion_importance		1.401	3.772		-74.50	-124.8
		(0.729)	(0.331)		(0.851)	(0.777)
q1_graph_right			72.10***			15.37
			(0.000)			(0.983)
q2_graph_right			44.29***			1661.8*
			(0.000)			(0.068)
q3_graph_right			-19.88**			939.9
			(0.024)			(0.356)
climate_U1right			53.46***			847.3
			(0.000)			(0.595)
right_GHGs			12.03**			-1283.7
			(0.022)			(0.205)
climate_U3right			0.442			547.5
			(0.960)			(0.687)
climate_U4right			4.131			-1136.7
			(0.659)			(0.242)
climate_U5right			-0.784			450.9
			(0.927)			(0.740)
arousal			0.0738			-43.83
			(0.691)			(0.196)
pleasure			0.0638			42.31
			(0.754)			(0.218)
Constant	102.1	169.4**	-37.40	-1714.2	2124.4	2244.6
	(0.171)	(0.019)	(0.507)	(0.345)	(0.609)	(0.558)
Observations	974	955	949	974	955	949
R^2	0.153	0.175	0.241	0.015	0.021	0.030

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 3

The Scale of Covid-19 Graphs Affects Understanding, Attitudes, and Policy Preferences

3.1 Introduction

The coronavirus disease 2019 (Covid-19) pandemic is a formidable challenge. Absent a cure or a vaccine, it is crucial that people are adequately informed about the pandemic (Everett et al., 2020), so that they stand behind policies that aim to minimise the spread of the virus and adopt behaviours that can limit the risk of contagion (Bursztyn et al., 2020). However, research has shown the challenges of communicating scientific facts in a way that effectively conveys essential information to the general public (Pidgeon and Fischhoff, 2011). In this article, we highlight the importance of this problem by focusing on one of the most basic pieces of information relative to the pandemic: the number of deaths. To provide information on the diffusion of the virus, mass media routinely publish graphs that depict the evolution in the number of Covid-19 related deaths in a given area. Many of these graphs present quantities on the Y-axis on either a linear scale (The Washington Post, 2020; Lopez, 2020) or a logarithmic scale (The Guardian, 2020; Financial Times, 2020; New York Times, 2020b). The New York Times, for instance, has explained that the logarithmic scale helps better visualise exponential growth (New York Times, 2020a). This follows advice given by epidemiology journals (Gladen and Rogan, 1983; Levine et al., 2010) and data visualisation handbooks (Kosslyn, 2006). However, what might be true for conveying information among experts might not hold when issuing information to a broader audience. The principle that logarithmic scales are better suited for exponential growth does not hold true if readers do not, in fact, comprehend them.

We show that scale choice has important consequences on how people understand and react to the information conveyed. In particular, we find that when people are exposed to a logarithmic scale they have a less accurate understanding of how the pandemic unfolded until now, make less accurate predictions on its future trajectory, and have different attitudes and policy preferences than when they are exposed to a linear scale. Another study (Ryan and Evers, 2020) carried out a week after ours, confirms our finding that the scale of the graph affects policy preferences and that people have problems understanding logarithms. Instead, a study with Canadian respondents finds that the scale of the graph has no impact on respondents (Sevi et al., 2020).[1] Previous studies have already shown that even experts have problems understanding graphs that use the logarithmic scale (Menge et al., 2018; Heckler et al., 2013). However, unlike most studies on graph comprehension we test understanding of graphs that represents real world highly salient data about which the public is likely to have ample background information and to care deeply. The obvious relevance of the data depicted in the graphs also allows us to test the impact of the scale in which the data is plotted on preferences about important policy issues. Since providing the public with clear information can help improving the response to Covid-19 (Bavel et al., 2020), mass media and policymakers should present data on the evolution of the pandemic using a graph on a linear scale, at least as a default option.

3.2 Experiment

We devised a double-blind experiment approved by the Yale IRB to test people's graph comprehension and its effects on attitudes and policy preferences. We recruited a sample of approximately $n = 2000$ (after exclusion criteria, with no regression with less than 1825 observations) U.S. residents on Cloud Research. Half of them were randomly assigned to the Linear Group, in which they were shown the evolution of Covid-19 deaths in the U.S. on a linear scale. The other half were assigned to the Log Group, in which participants saw the same data, but plotted on a logarithmic scale. The graphs were taken from the popular website www.worldometers.info (See Fig 3.1). We asked respondents three sets of questions: (*i*) attitudes and policy preferences, (*ii*) graph understanding, and (*iii*) standard demographic questions. In the Appendix, we report the questions we asked and the order in which they were asked.

The analyses can be grouped into: 1) determinants of worry, 2) policy preferences and 3) differences in understanding. In all three cases our primary variable of interest is "linear",

[1] However, their study uses a "catch all" question for pessimism and one on policy preferences. These catch all questions might be unable to capture the nuanced impact of graph scale on policies and attitudes that we observe. For instance, we observe an impact on worry for the health crisis, but *not* on worry for the economic crisis.

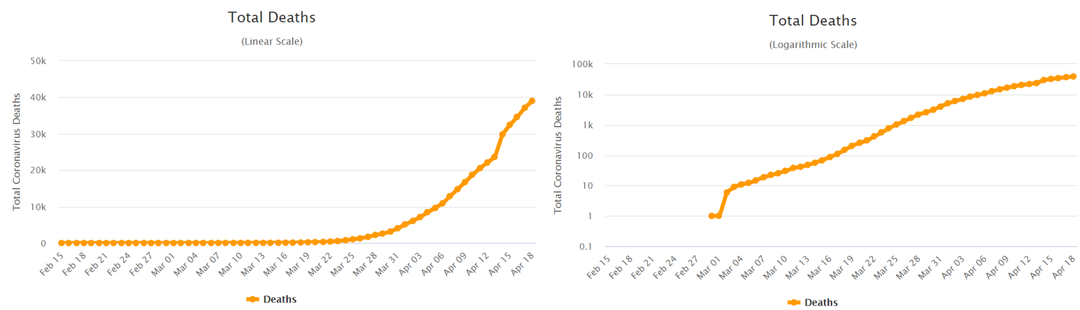

Figure 3.1: Covid-19 Related Deaths in United States Between February 15th and April 18th in a linear scale (left panel) and in a log scale (right panel). Source: www.worldometers.info

a binary taking value 1 whenever the participant was exposed to the linear scale graphs, and 0 otherwise.

We start by showing participants in the two groups the graph plotting the evolution of the total number of deaths on the scale to which they were randomly assigned. Then we ask respondents in the two groups to indicate how worried they are about the health crisis and the economic crisis caused by Covid-19 on a five points Likert scale from "not worried at all" to "extremely worried". Second, we ask respondents about their preferences on some policies that many States have adopted to mitigate the spread of Covid-19. In the first pair of policy questions we ask whether they support the policy of closing non-essential businesses (five points Likert scale from "strongly disagree" to "strongly agree"), and until which date they would keep these businesses closed. In the second pair of policy questions we ask participants how often they would use a mask if the government sent a supply (five points Likert scale from "never" to "always"). Moreover, we ask whether they would support a tax that finances the distribution of masks for everyone in their State (five points Likert scale from "strongly oppose" to "strongly support").

We then turn to test respondents' understanding of the graphs. To increase external validity and to avoid priming respondents, we ask attitudes and policy preferences *before* testing understanding. This allows us to obtain respondents' policy preferences before they are asked to think thoroughly about the graph and its meaning in a way that they would be unlikely to do when reading actual news.

We test understanding of graphs by asking three questions. First, we show them the Covid-19 graph on the scale that they had been assigned and ask them whether the number of deaths increased more between March 31st and April 6th or between April 6th and April 12th. Second, we show them a graph describing non-Covid-19 related data on the number of deaths from an hypothetical infection Z taken from Okan et al. (2016) and asked them a similar question. As for the first graph shown to participants, people in the Linear Group saw the data plotted on a linear scale, whereas respondents in the Log Group saw data plotted on a logarithmic one. The goal of this question was to test whether respondents' ability to answer correctly the first question depended on prior information on Covid-19, or on a correct understanding of the scale on which their graphs are plotted.

Predicting the number of Covid-19 related deaths in a week is very difficult, but some predictions are more reasonable than others. We forecast the number of total deaths on April 25th using an ARIMA model, a standard forecasting method that has already been used to predict Covid-19 diffusion (Benvenuto et al., 2020). We use a ARIMA (0,2,1), as simulations show that it offers the best fit for the data, and forecast the number of cases and its 95% and 99% confidence intervals (CIs). On the 18th of April the number of deaths was $39,014$. The 95% CI forecasted using the ARIMA(0,2,1) ranges from $49,203.15$ to $62,559.27$, whereas the 99% CI ranges from $46,895.47$ to $64,685.95$. We remark that the actual number of deaths on the 25th of April was $54,256$, while our ARIMA predicted $55,791$ deaths predicted model. This is well within the CIs we consider.

We use these CIs to divide predictions in three groups. In the first group, we include the predictions that fall within the forecast 95% confidence interval ("accurate range"). We consider these predictions "accurate". In the second group, we include the predictions that fall within the 99% confidence interval, but outside the 95% confidence interval ("unlikely range"). We refer to these predictions as "unlikely". Last, we consider the predictions that fall outside the 99% confidence interval ("unreasonable range") as "unreasonable".

Additionally, for each of the understanding questions we asked how confident respondents were about their answers. The level of confidence is important as it can shed some light on how much weight people will attach to the information represented in the graph.

We concluded by collecting standard demographic information on the respondents.

3.3 Results and Discussion

Table 3.1 describes the characteristics of our sample. Figures 3.2 and 3.3 and Tables 3.2-3.3 show that people in the Linear Group understand the graphs better and make better predictions. The Log Group gives predictions that are higher and are on average unreasonable. Therefore, using linear scale graphs reduces the risk of confusing the public.

Moreover, the scale also impacts people level of worry for the health crisis (but not for the economic crisis) and their policy preferences. People in the Linear Group are more

	Graph shown								
	Log Scale			Linear Scale			Total		
	No.	Col %	Cum %	No.	Col %	Cum %	No.	Col %	Cum %
Age									
18-25 years old	126	11.6	11.6	122	12.4	12.4	248	12.0	12.0
26-35 years old	351	32.3	43.9	309	31.3	43.7	660	31.8	43.8
36-45 years old	234	21.5	65.4	237	24.0	67.7	471	22.7	66.5
46-55 years old	182	16.7	82.2	150	15.2	82.9	332	16.0	82.5
56-65 years old	129	11.9	94.0	107	10.8	93.7	236	11.4	93.9
66-75 years old	57	5.2	99.3	52	5.3	99.0	109	5.3	99.1
>75 years old	8	0.7	100.0	10	1.0	100.0	18	0.9	100.0
Education									
Less than high school degree	4	0.4	0.4	5	0.5	0.5	9	0.4	0.4
High school graduate (diploma or equivalent)	88	8.1	8.5	83	8.4	8.9	171	8.3	8.7
Some college but no degree	210	19.3	27.8	168	17.0	26.0	378	18.2	26.9
Associate degree in college (2-year)	97	8.9	36.7	101	10.2	36.2	198	9.6	36.5
Bachelor's degree in college	478	44.0	80.8	402	40.8	77.0	880	42.5	79.0
Master's or Professional Degree (JD, MD, etc)	190	17.5	98.3	203	20.6	97.6	393	19.0	97.9
Doctoral degree	19	1.7	100.0	24	2.4	100.0	43	2.1	100.0
Income									
Less than $10,000	48	4.4	4.4	36	3.7	3.7	84	4.1	4.1
$10,000 to $19,999	64	5.9	10.3	56	5.7	9.3	120	5.8	9.9
$20,000 to $29,999	75	6.9	17.2	96	9.8	19.1	171	8.3	18.1
$30,000 to $39,999	120	11.1	28.3	88	8.9	28.0	208	10.1	28.2
$40,000 to $49,999	108	10.0	38.2	104	10.6	38.6	212	10.2	38.4
$50,000 to $59,999	111	10.2	48.5	103	10.5	49.1	214	10.3	48.8
$60,000 to $69,999	100	9.2	57.7	85	8.6	57.7	185	8.9	57.7
$70,000 to $79,999	100	9.2	66.9	75	7.6	65.3	175	8.5	66.2
$80,000 to $89,999	58	5.3	72.3	68	6.9	72.3	126	6.1	72.3
$80,000 to $89,999	60	5.5	77.8	71	7.2	79.5	131	6.3	78.6
$90,000 to $99,999	164	15.1	92.9	128	13.0	92.5	292	14.1	92.7
$150,000 or more	77	7.1	100.0	74	7.5	100.0	151	7.3	100.0
Political orientation									
Other	352	32.4	32.4	292	29.6	29.6	644	31.1	31.1
Democrat	441	40.6	73.0	426	43.2	72.7	867	41.8	72.9
Republican	294	27.0	100.0	269	27.3	100.0	563	27.1	100.0
Total	1087	100.0		987	100.0		2074	100.0	
Gender									
Other/Prefer not to declare	8	0.7	0.7	14	1.4	1.4	22	1.1	1.1
Female	571	52.5	53.3	524	53.1	54.5	1095	52.8	53.9
Male	508	46.7	100.0	449	45.5	100.0	957	46.1	100.0
Live in city with <50K People									
No	680	62.6	62.6	601	60.9	60.9	1281	61.8	61.8
Yes	407	37.4	100.0	386	39.1	100.0	793	38.2	100.0
Total	1087	100.0		987	100.0		2074	100.0	
Live in city with >500K People									
No	851	78.3	78.3	769	77.9	77.9	1620	78.1	78.1
Yes	236	21.7	100.0	218	22.1	100.0	454	21.9	100.0

Table 3.1: Frequency Table for Demographic Variables: Number, Percentage and Cumulative Percentage of respondents for the following variables: Age, Education, Income, Political orientation, Gender, Live in city with less than 50K people, Live in city with more than 500K people. Column 1 shows the distribution for the Log Group, Column 2 shows the distribution for the Linear Group and Column 3 the overall one.

	(1) Understanding Q.1: Real Data	(2) Understanding Q.1: Real Data	(3) Understanding Q.2: Hypothetical	(4) Understanding Q.2: Hypothetical
In Linear Group	2.021***	2.054***	4.634***	4.819***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Confidence in Understanding Q.1		0.00886***		
		(<0.001)		
Worry About Health Crisis		-0.0310		-0.0851
		(0.585)		(0.318)
COVID-19 News Checking		0.0780		0.0860
		(0.145)		(0.290)
Education		0.0213		0.152**
		(0.619)		(0.021)
Male		-0.147		0.321*
		(0.193)		(0.066)
Age		0.00445		0.0154**
		(0.268)		(0.012)
Democrat		0.00380		0.0870
		(0.977)		(0.660)
Republican		-0.0190		-0.183
		(0.895)		(0.413)
Confidence in Understanding Q.2				0.0308***
				(<0.001)
Constant	-0.378***	-1.375***	-2.164***	-6.119***
	(<0.001)	(0.001)	(<0.001)	(<0.001)
Observations	2074	1830	2074	1830

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.2: Understanding questions: The coefficients are estimated through a Logit regression. P-values are reported in parentheses. The standard errors can be found in the Appendix. Columns 1 and 2: Right answer to the question on the understanding question on COVID-19 data. Columns 3 and : Right answer to question on Infection Z (hypothetical data). P-values are reported in parentheses. Standard errors for the same tables can be found in the Appendix. All coefficients for the control variables are reported.

	(1) Accurate Prediction	(2) Accurate Prediction	(3) Unreasonable Prediction	(4) Unreasonable Prediction
In Linear Group	0.489***	0.482***	-0.481***	-0.480***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Confidence in Prediction		-0.00178		0.00188
		(0.447)		(0.411)
Worry About Health Crisis		-0.0112		0.0494
		(0.830)		(0.327)
COVID-19 News Checking		0.150***		-0.175***
		(0.002)		(<0.001)
Education		0.0477		-0.0461
		(0.221)		(0.224)
Male		-0.0327		-0.0149
		(0.749)		(0.881)
Age		0.00182		-0.00480
		(0.616)		(0.175)
Democrat		0.0920		-0.106
		(0.437)		(0.360)
Republican		-0.181		0.221*
		(0.172)		(0.087)
Constant	-0.848***	-1.378***	0.585***	1.147***
	(<0.001)	(<0.001)	(<0.001)	(0.001)
Observations	2074	1832	2074	1832

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3: Determinants of making an accurate prediction (Columns 1 and 2) and an unreasonable prediction (Columns 3 and 4). The coefficients are estimated through Logit regressions. P-values are reported in parentheses. The standard errors can be found in the Appendix. All coefficients for the control variables are reported.

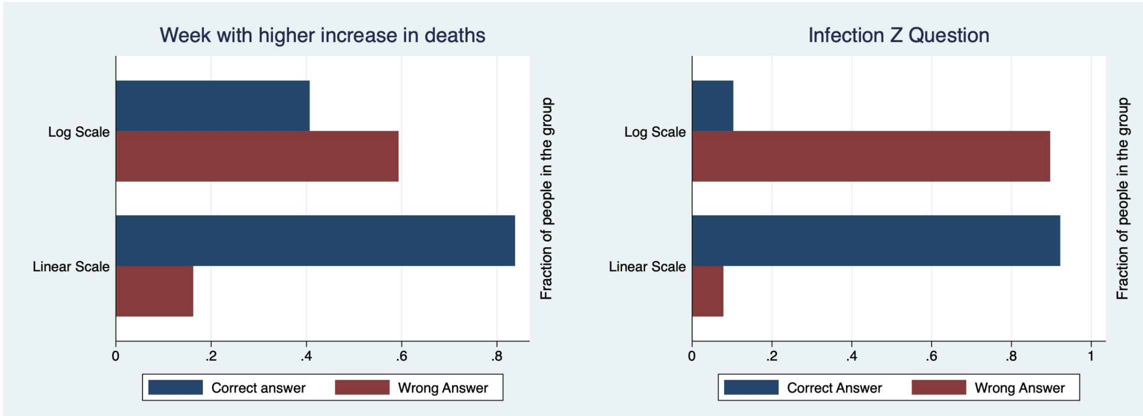

Figure 3.2: The left panel reports the percentage of correct and incorrect answers provided by the members of the two groups to the understanding question related to Covid-19 real world data. The right panel reports the percentage of correct and incorrect answers provided by the members of the two groups to the understanding question related to Infection Z hypothetical data.

worried about the health crisis (see Table 3.4), and prefer that non-essential businesses remain closed for longer (Table 3.5).

However, they support less strongly the idea of closing non-essential business in the first place (Table 3.5), and would wear government-supplied masks less often (Table 3.6). These results are statistically significant and robust to a series of different controls and specifications (the regressions presented use Logit and OLS and the results are robust to different sets of controls). The odds ratios show that the magnitude of the effects is non-negligible (Table 3.7).

These findings are remarkable because the data underlying the graphs is identical. Merely changing the scale can alter public policy preferences and the level of worry, despite the endless flow of Covid-19 related information to which everyone is exposed.

We cannot know the mechanism leading to these preferences, but we advance the conjecture that the shape of the curves could explain these findings. The flat logarithmic curve can give the impression that we reached a plateau and that, while the present situation is very serious, things are about to get better soon. Thus respondents in the Log Group might be less worried because they feel that the end of the pandemic is near. For the same reason, they could strongly support closing non essential businesses now, i.e., during the peak, but could want to reopen them as soon as the peak is over. Moreover, they might concentrate the use of masks during the peak. As the Log Group thinks we are at the peak, they could

	(1) Worry About Health Crisis	(2) Worry About Health Crisis	(3) Worry About Health Crisis
Worry About Health Crisis			
In Linear Group	0.141*	0.258*	0.327**
	(0.081)	(0.091)	(0.038)
COVID-19 News Checking		0.500***	0.434***
		(<0.001)	(<0.001)
Male		-0.806***	-0.654***
		(<0.001)	(<0.001)
Understanding Q.1: Real Data		-0.00425	0.00558
		(0.967)	(0.958)
Confidence in Understanding Q.1		-0.00134	-0.00152
		(0.706)	(0.674)
Understanding Q.2: Hypothetical		-0.137	-0.225
		(0.386)	(0.171)
Confidence in Understanding Q.2		-0.00374	-0.00428
		(0.302)	(0.246)
Accurate Prediction		0.156	0.218
		(0.404)	(0.255)
Unreasonable Prediction		0.225	0.325*
		(0.216)	(0.084)
Confidence in Prediction		0.00622***	0.00579***
		(0.005)	(0.009)
Democrat			0.732***
			(<0.001)
Republican			-0.282**
			(0.017)
Worry About Economic Crisis			0.707***
			(<0.001)
Live in city with <50K People			0.0156
			(0.880)
Live in city with >500K People			-0.132
			(0.280)
Education			-0.0258
			(0.473)
Age			-0.00132
			(0.694)
State of Residence			0.00777**
			(0.030)
Restrictions in the State			-0.156
			(0.160)
Observations	2074	1837	1828

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.4: Determinants of worry about health crisis caused by Covid-19. The coefficients are estimated through ordered Logit regressions. P-values are reported in parentheses. Standard errors can be found in the Appendix. All coefficients for the control variables are reported.

	(1)	(2)	(3)	(4)	(5)	(6)
	Support for	Support for	Support for	Days Until	Days Until	Days Until
Closing Businesses	Closing Businesses	Closing Businesses	Reopening Businesses	Reopening Businesses	Reopening Businesses	
In Linear Group	0.0406	-0.378**	-0.424**	2.295	17.38**	14.65**
	(0.621)	(0.019)	(0.012)	(0.464)	(0.014)	(0.037)
Worry About Health Crisis		0.997***	1.067***		12.45***	13.14***
		(<0.001)	(<0.001)		(<0.001)	(<0.001)
COVID-19 News Checking		0.0288	0.0748		3.071*	3.932**
		(0.531)	(0.117)		(0.056)	(0.018)
Male		-0.112	-0.0890		10.53***	9.169***
		(0.242)	(0.366)		(0.002)	(0.006)
Understanding Q.1: Real Data		0.131	0.132		-1.236	-0.517
		(0.228)	(0.236)		(0.762)	(0.900)
Confidence in Understanding Q.1		0.00955***	0.00842**		0.109	0.0996
		(0.009)	(0.023)		(0.391)	(0.440)
Understanding Q.2: Hypothetical		0.300*	0.348**		-18.05**	-15.87**
		(0.075)	(0.047)		(0.012)	(0.026)
Confidence in Understanding Q.2		-<0.001421	-<0.001228		-0.310**	-0.299**
		(0.911)	(0.952)		(0.025)	(0.032)
Accurate Prediction		0.480**	0.450**		10.58*	9.343
		(0.012)	(0.019)		(0.093)	(0.138)
Unreasonable Prediction		0.0871	0.0806		6.590	4.787
		(0.635)	(0.665)		(0.277)	(0.431)
Confidence in Prediction		-0.00451*	-0.00426*		0.216***	0.205**
		(0.054)	(0.073)		(0.007)	(0.012)
Democrat			0.545***			0.107
			(<0.001)			(0.977)
Republican			-0.491***			1.912
			(<0.001)			(0.683)
Worry About Economic Crisis			-0.494***			-3.597*
			(<0.001)			(0.069)
Live in city with <50K People			0.0314			6.259*
			(0.770)			(0.085)
Live in city with >500K People			0.0230			9.164**
			(0.858)			(0.037)
Education			-0.0258			-1.798
			(0.496)			(0.173)
Age			-0.00105			-0.151
			(0.769)			(0.192)
State of Residence			0.00274			-0.00686
			(0.456)			(0.957)
Restrictions in the State			-0.0175			-1.382
			(0.881)			(0.741)
In Linear Group						0
						(.)
Constant				65.38***	-0.312	24.09
				(<0.001)	(0.979)	(0.155)
Observations	2074	1837	1828	2061	1828	1819

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.5: Determinants for support for keeping shops closed (Columns 1-3) and suggested reopening day (Columns 4-6). Columns 1-3 report coefficients estimated through ordered Logit regressions and Columns 4-6 report coefficients obtained through ordinary least squares regressions (OLS). P-values are reported in parentheses. The standard errors can be found in the Appendix. All coefficients for the control variables are reported

	(1) Likelihood to Wear Masks	(2) Likelihood to Wear Masks	(3) Likelihood to Wear Masks	(4) Support for Mask-Buying Tax	(5) Support for Mask-Buying Tax	(6) Support for Mask-Buying Tax
In Linear Group	0.00311	-0.314**	-0.350**	-0.0218	0.307**	0.305**
	(0.970)	(0.045)	(0.029)	(0.780)	(0.042)	(0.046)
Worry About Health Crisis		0.907***	0.908***		0.481***	0.471***
		(<0.001)	(<0.001)		(<0.001)	(<0.001)
COVID-19 News Checking		0.138***	0.129***		0.0403	0.0682
		(0.003)	(0.006)		(0.341)	(0.116)
Male		-0.255***	-0.270***		0.0372	0.0455
		(0.007)	(0.005)		(0.673)	(0.612)
Understanding Q.1: Real Data		0.0281	0.0136		0.152	0.169*
		(0.796)	(0.902)		(0.133)	(0.097)
Confidence in Understanding Q.1		0.00571	0.00493		0.00648*	0.00602*
		(0.125)	(0.192)		(0.065)	(0.088)
Understanding Q.2: Hypothetical		0.189	0.237		-0.454***	-0.452***
		(0.249)	(0.157)		(0.004)	(0.004)
Confidence in Understanding Q.2		0.00250	0.00272		-0.0108***	-0.0112***
		(0.510)	(0.479)		(0.003)	(0.002)
Accurate Prediction		0.435**	0.431**		0.186	0.141
		(0.020)	(0.022)		(0.312)	(0.444)
Unreasonable Prediction		0.497***	0.493***		0.165	0.147
		(0.007)	(0.007)		(0.357)	(0.414)
Confidence in Prediction		0.00211	0.00276		0.00675***	0.00734***
		(0.352)	(0.231)		(0.002)	(0.001)
Democrat			0.161			0.378***
			(0.154)			(<0.001)
Republican			-0.384***			-0.261**
			(0.001)			(0.024)
Worry About Economic Crisis			-0.132**			-0.0979*
			(0.021)			(0.069)
Live in city with <50K People			0.0832			0.115
			(0.424)			(0.240)
Live in city with >500K People			0.588***			0.0488
			(<0.001)			(0.681)
Education			-0.0767**			-0.0209
			(0.040)			(0.543)
Age			0.00713**			-0.00942***
			(0.041)			(0.004)
State of Residence			0.0170***			-0.00313
			(<0.001)			(0.358)
Restrictions in the State			-0.154			-0.122
			(0.177)			(0.258)
Likelihood to Wear Masks					0.648***	0.617***
					(<0.001)	(<0.001)
Observations	2072	1835	1826	2072	1834	1825

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.6: Determinants of likelihood to wear a mask when going out if provided with one (Columns 1-3) and supporting a tax to finance their distribution (Columns 4-6). The coefficients are estimated through ordered Logit regressions. P-values are reported in parentheses. The standard errors can be found in the Appendix. All coefficients for the control variables are reported.

	(1) Worry About Health Crisis	(2) Likelihood to Wear Masks	(3) Support for Mask-Buying Tax	(4) Support for Closing Businesses	(5) Understanding Q.1: Real Data	(6) Understanding Q.2: Hypothetical	(7) Accurate Prediction	(8) Unreasonable Prediction
In Linear Group	1.387*	0.705*	1.356*	0.654*	7.800***	123.9***	1.619***	0.619***
	(0.218)	(0.113)	(0.207)	(0.110)	(0.902)	(23.13)	(0.159)	(0.0594)
COVID-19 News Checking	1.543***	1.138**	1.071	1.078	1.081	1.090	1.162**	0.840***
	(0.0718)	(0.0537)	(0.0464)	(0.0514)	(0.0578)	(0.0886)	(0.0563)	(0.0398)
Male	0.520***	0.763**	1.047	0.915	0.864	1.379	0.968	0.985
	(0.0486)	(0.0735)	(0.0937)	(0.0900)	(0.0972)	(0.241)	(0.0988)	(0.0980)
Understanding Q.1: Real Data	1.006	1.014	1.184	1.141				
	(0.107)	(0.112)	(0.120)	(0.127)				
Confidence in Understanding Q.1	0.998	1.005	1.006	1.008*	1.009***			
	(0.00361)	(0.00379)	(0.00355)	(0.00375)	(0.00253)			
Understanding Q.2: Hypothetical	0.799	1.267	0.636**	1.416*				
	(0.131)	(0.212)	(0.101)	(0.247)				
Confidence in Understanding Q.2	0.996	1.003	0.989**	1.000		1.031***		
	(0.00368)	(0.00385)	(0.00360)	(0.00379)		(0.00424)		
Accurate Prediction	1.244	1.539*	1.152	1.569*				
	(0.238)	(0.290)	(0.213)	(0.302)				
Unreasonable Prediction	1.384	1.638**	1.159	1.084				
	(0.260)	(0.301)	(0.209)	(0.202)				
Confidence in Prediction	1.006**	1.003	1.007***	0.996			0.998	1.002
	(0.00225)	(0.00231)	(0.00221)	(0.00236)			(0.00234)	(0.00229)
Democrat	2.080***	1.175	1.459***	1.725***	1.004	1.091	1.096	0.900
	(0.225)	(0.133)	(0.152)	(0.200)	(0.131)	(0.216)	(0.130)	(0.104)
Republican	0.754*	0.681**	0.770*	0.612***	0.981	0.833	0.834	1.247
	(0.0893)	(0.0822)	(0.0891)	(0.0735)	(0.141)	(0.186)	(0.111)	(0.161)
Worry About Economic Crisis	2.028***	0.876*	0.907	0.610***				
	(0.112)	(0.0502)	(0.0488)	(0.0374)				
Live in city with <50K People	1.016	1.087	1.122	1.032				
	(0.105)	(0.113)	(0.110)	(0.111)				
Live in city with >500K People	0.876	1.801***	1.050	1.023				
	(0.107)	(0.233)	(0.124)	(0.132)				
Education	0.975	0.926*	0.979	0.975	1.022	1.164*	1.049	0.955
	(0.0350)	(0.0347)	(0.0338)	(0.0369)	(0.0438)	(0.0768)	(0.0409)	(0.0362)
Age	0.999	1.007*	0.991**	0.999	1.004	1.016*	1.002	0.995
	(0.00336)	(0.00352)	(0.00322)	(0.00355)	(0.00403)	(0.00624)	(0.00363)	(0.00352)
State of Residence	1.008*	1.017***	0.997	1.003				
	(0.00362)	(0.00402)	(0.00339)	(0.00368)				
Restrictions in the State	0.855	0.857	0.885	0.983				
	(0.0951)	(0.0978)	(0.0957)	(0.115)				
Worry About Health Crisis		2.480***	1.602***	2.907***	0.969	0.918	0.989	1.051
		(0.136)	(0.0862)	(0.165)	(0.0550)	(0.0782)	(0.0513)	(0.0530)
Likelihood to Wear Masks			1.854***					
			(0.0935)					
Observations	1828	1826	1825	1828	1830	1830	1832	1832

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** < 0.001

Table 3.7: The table reports Odds Ratios for Logit Regressions: Worry About Health Crisis, Likelihood to Wear Masks, Support for Mask-Buying Tax, Support for Closing Businesses, Understanding Q.1: Real Data, Understanding Q.2: Hypothetical, Accurate Prediction, Unreasonable Prediction. The controls used in each of these regression are the same as in the last column of each regression in Tables 2-6.

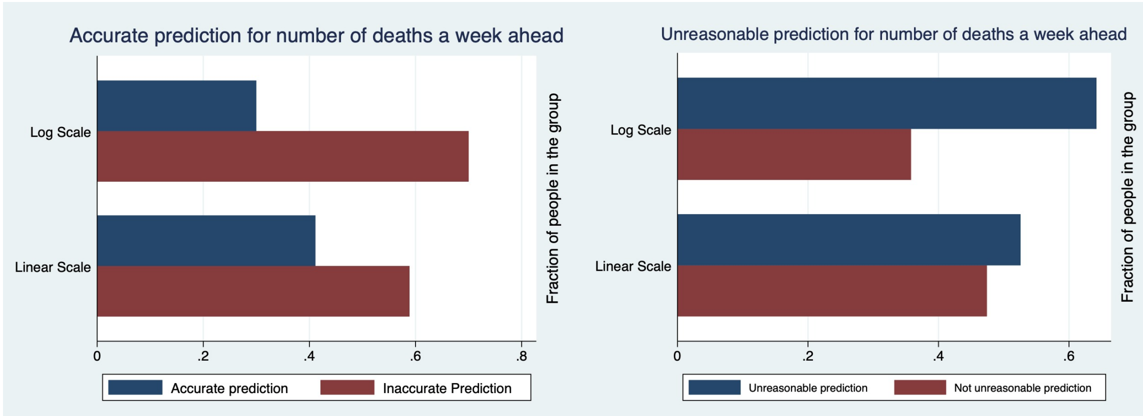

Figure 3.3: The left panel reports the percentage of accurate and inaccurate (i.e., not accurate) predictions provided by the members of the two groups. The right panel reports the unreasonable and reasonable (i.e., not unreasonable) predictions provided by the members of the two groups.

also expect a very high number of deaths in the short term, which would also explain their strong support to wear masks and to keep business closed.

Vice versa, the linear curve is constantly growing with no sign of improvement, hence it might give the impression that the crisis will go on for long and will be very serious. Consequently, people in the Linear Group might be more worried and wish to reopen non-essential businesses later. However, they could support closing non-essential businesses relatively less, because they believe that the pandemic will last for a long time, and non-essential businesses cannot remain closed for too long. However, if the decision taken is to close non-essential businesses, they might feel that it would be pointless to do it for a short period of time. They would apply a similar logic to masks. As they believe that the pandemic will last for a long time, they could use them less frequently to ration them.

Regardless of the reasons behind our findings, it is noteworthy that changing the scale can alter policy preferences, intentions to adopt precautionary measures, and level of worry for the health consequences of the pandemic. Given that the scale affects policy preferences and that people have significant problems understanding the logarithmic scale, our findings suggests that representing data on a linear scale is preferable. Garfin et al. (2020) noted that during a public health crisis, the general public relies on the media to convey accurate and understandable information, so that it can take informed decisions regarding health protective behaviours. Absent information of this kind, people cannot form informed preferences or take informed decisions. Moreover, unclear information conveyed by the media could undermine how much people trust science, which is a key predictor of compliance with Covid-19 guidelines (Brzezinski et al., 2020; Plohl and Musil, 2021).

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3.A Appendix

In the appendix we include additional tables that expand on the results presented in the article and the full questionnaire.

Table 3.A.1: Summary statistics (mean and standard deviation (SD)) for the variables considered in the regression tables. These include: Worry About Health Crisis, Worry About Economic Crisis, Days Until Reopening Businesses, Support for Closing Businesses, Likelihood to Wear Masks and Support for a Mask-Buying Tax. Column 1 presents the statistics for all participants, Column 2 only for the Linear Group and Column 3 only for the Log Group.

	All Sample		Linear Group		Log Group	
	mean	SD	mean	SD	mean	SD
Worry About Health Crisis	3.98	1.07	4.03	1.05	3.94	1.10
Worry About Economic Crisis	4.25	0.90	4.27	0.86	4.23	0.93
Days Until Reopening Businesses	66.47	71.01	67.67	71.19	65.38	70.87
Support for Closing Businesses	4.08	1.16	4.09	1.16	4.07	1.17
Likelihood to Wear Masks	4.09	1.10	4.10	1.09	4.09	1.10
Support for Mask-Buying Tax	3.25	1.38	3.24	1.38	3.25	1.39
Observations	2074		987		1087	

Table 3.A.2: Determinants of answering the understanding question on COVID-19 data (Columns 1-4) and the understanding question on Infection Z (hypothetical data) (Columns 5-8) correctly. Columns 1, 2, 5 and 6 report coefficients estimated through Logit regressions, Columns 3, 4, 7 and 8 report coefficients estimated through Probit regressions. Standard errors are reported in parentheses. All coefficients for the control variables are reported.

	(1) Q1: Real Data	(2) Q1: Real Data	(3) Q1: Real Data	(4) Q1: Real Data	(5) Q2: Hypothetical	(6) Q2: Hypothetical	(7) Q2: Hypothetical	(8) Q2: Hypothetical
In Linear Group	2.021***	2.054***	1.222***	1.241***	4.634***	4.819***	2.683***	2.733***
	(0.106)	(0.116)	(0.0613)	(0.0664)	(0.155)	(0.187)	(0.0779)	(0.0899)
Confidence in Q1		0.00886***		0.00560***				
		(0.00251)		(0.00147)				
Worry About Health Crisis		-0.0310		-0.0201		-0.0851		-0.0492
		(0.0568)		(0.0339)		(0.0852)		(0.0450)
COVID-19 News Checking		0.0780		0.0430		0.0860		0.0457
		(0.0535)		(0.0317)		(0.0813)		(0.0420)
Education		0.0213		0.0152		0.152**		0.0795**
		(0.0429)		(0.0254)		(0.0659)		(0.0341)
Male		-0.147		-0.0875		0.321*		0.160*
		(0.113)		(0.0670)		(0.175)		(0.0895)
Age		0.00445		0.00261		0.0154**		0.00748**
		(0.00401)		(0.00239)		(0.00614)		(0.00317)
Democrat		0.00380		-0.00114		0.0870		0.0302
		(0.130)		(0.0778)		(0.198)		(0.103)
Republican		-0.0190		-0.0140		-0.183		-0.0992
		(0.144)		(0.0856)		(0.223)		(0.115)
Confidence in Q2						0.0308***		0.0148***
						(0.00411)		(0.00204)
Constant	-0.378***	-1.375***	-0.236***	-0.843***	-2.164***	-6.119***	-1.264***	-3.136***
	(0.0617)	(0.407)	(0.0384)	(0.240)	(0.0998)	(0.665)	(0.0514)	(0.334)
Observations	2074	1830	2074	1830	2074	1830	2074	1830
Adjusted R^2								

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.A.3: Determinants of making an accurate prediction (Columns 1-4) and an unreasonable prediction (Columns 5-8). The coefficients estimated through Logit regressions (Columns 1, 2, 5 and 6) and a Probit regressions (Columns 3, 4, 7 and 8). Standard errors in parentheses. All coefficients for the control variables are reported.

Prediction	(1) Accurate Prediction	(2) Accurate Prediction	(3) Accurate Prediction	(4) Accurate Prediction	(5) Unreasonable Prediction	(6) Unreasonable Prediction	(7) Unreasonable Prediction	(8) Unreasonable Prediction
In Linear Group	0.489***	0.482***	0.301***	0.297***	-0.481***	-0.480***	-0.299***	-0.299***
	(0.0926)	(0.0985)	(0.0567)	(0.0605)	(0.0898)	(0.0961)	(0.0558)	(0.0596)
Confidence in Prediction		-0.00178		-0.00110		0.00188		0.00117
		(0.00234)		(0.00144)		(0.00228)		(0.00142)
Worry About Health Crisis		-0.0112		-0.00652		0.0494		0.0300
		(0.0519)		(0.0318)		(0.0504)		(0.0313)
COVID-19 News Checking		0.150***		0.0931***		-0.175***		-0.109***
		(0.0484)		(0.0298)		(0.0474)		(0.0294)
Education		0.0477		0.0295		-0.0461		-0.0288
		(0.0390)		(0.0239)		(0.0379)		(0.0236)
Male		-0.0327		-0.0201		-0.0149		-0.00876
		(0.102)		(0.0627)		(0.0995)		(0.0617)
Age		0.00182		0.00113		-0.00480		-0.00300
		(0.00363)		(0.00223)		(0.00354)		(0.00220)
Democrat		0.0920		0.0573		-0.106		-0.0657
		(0.118)		(0.0728)		(0.116)		(0.0718)
Republican		-0.181		-0.110		0.221*		0.137*
		(0.133)		(0.0812)		(0.129)		(0.0797)
Constant	-0.848***	-1.378***	-0.525***	-0.857***	0.585***	1.147***	0.364***	0.719***
	(0.0662)	(0.346)	(0.0400)	(0.212)	(0.0633)	(0.337)	(0.0389)	(0.209)
Observations	2074	1832	2074	1832	2074	1832	2074	1832
Adjusted R^2								

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.A.4: Determinants of Economythe Worry caused by Covid-19. The coefficients are estimated through ordered Logit regressions (Columns 1-3), ordered Probit regressions (Columns 4-6) and Ordinary Least Squares (OLS) regressions (Columns 7-9). Standard errors are reported in parentheses. All coefficients for the control variables are reported.

	(1) Economy Worry	(2) Economy Worry	(3) Economy Worry	(4) Economy Worry	(5) Economy Worry	(6) Economy Worry	(7) Economy Worry	(8) Economy Worry	(9) Economy Worry
In Linear Group	0.0397	-0.116	-0.102	0.0372	-0.0387	-0.0331	0.0384	-0.0200	-0.0159
	(0.0828)	(0.161)	(0.163)	(0.0494)	(0.0928)	(0.0939)	(0.0393)	(0.0727)	(0.0733)
EconomyHealth Crisis		0.535***	0.598***		0.303***	0.341***		0.227***	0.250***
		(0.0492)	(0.0513)		(0.0274)	(0.0284)		(0.0256)	(0.0260)
COVID-19 News Checking		0.223***	0.214***		0.127***	0.119***		0.0822***	0.0764***
		(0.0453)	(0.0464)		(0.0267)	(0.0273)		(0.0184)	(0.0188)
Male		-0.0695	-0.0852		-0.0604	-0.0705		-0.0476	-0.0554
		(0.0943)	(0.0958)		(0.0554)	(0.0562)		(0.0405)	(0.0407)
Understanding Q.1: Real Data		-0.107	-0.116		-0.0802	-0.0844		-0.0652	-0.0677
		(0.108)	(0.109)		(0.0634)	(0.0638)		(0.0456)	(0.0456)
Confidence in Understanding Q.1		-0.0000464	0.000460		-0.0000710	0.000326		-0.000215	-0.0000115
		(0.00365)	(0.00369)		(0.00214)	(0.00216)		(0.00155)	(0.00156)
Understanding Q.2: Hypothetical		0.174	0.170		0.0950	0.0934		0.0685	0.0675
		(0.168)	(0.170)		(0.0972)	(0.0982)		(0.0740)	(0.0745)
Confidence in Understanding Q.2		-0.000656	-0.000441		-0.000524	-0.000551		-0.000289	-0.000261
		(0.00375)	(0.00378)		(0.00219)	(0.00220)		(0.00158)	(0.00161)
Accurate Prediction		-0.304	-0.289		-0.181	-0.172		-0.130*	-0.125
		(0.197)	(0.198)		(0.116)	(0.116)		(0.0763)	(0.0761)
Unreasonable Prediction		-0.256	-0.269		-0.163	-0.169		-0.125*	-0.128*
		(0.193)	(0.194)		(0.113)	(0.113)		(0.0748)	(0.0748)
Confidence in Prediction		0.000260	0.000311		-0.0000446	0.0000609		-0.000353	-0.000269
		(0.00226)	(0.00229)		(0.00133)	(0.00135)		(0.00100)	(0.00100)
Democrat			-0.294***			-0.175***			-0.128***
			(0.110)			(0.0649)			(0.0470)
Republican			0.231*			0.125*			0.0740
			(0.124)			(0.0724)			(0.0517)
Live in city with <50K People			-0.147			-0.0862			-0.0498
			(0.104)			(0.0614)			(0.0444)
Live in city with >500K People			0.0144			0.0227			0.0230
			(0.125)			(0.0735)			(0.0518)
Education			-0.0174			-0.00736			-0.00358
			(0.0367)			(0.0215)			(0.0153)
Age			0.00481			0.00309			0.00196
			(0.00343)			(0.00202)			(0.00139)
State of Residence			-0.000372			-0.000867			-0.000649
			(0.00353)			(0.00207)			(0.00160)
Restrictions in the State			0.233**			0.133*			0.0916**
			(0.115)			(0.0683)			(0.0465)
Constant							4.231***	3.321***	3.033***
							(0.0281)	(0.151)	(0.203)
Observations	2073	1837	1828	2073	1837	1828	2073	1837	1828
Adjusted R^2							-0.000	0.092	0.102

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.A.5: Determinants of worry about health crisis caused by COVID-19. The coefficients are estimated through ordered Logit regressions (Columns 1-3), ordered Probit regressions (Columns 4-6) and Ordinary Least Squares (OLS) regressions (Columns 7-9). Standard errors are reported in parentheses. All coefficients for the control variables are reported.

	(1) Worry About Health Crisis	(2) Worry About Health Crisis	(3) Worry About Health Crisis	(4) Worry About Health Crisis	(5) Worry About Health Crisis	(6) Worry About Health Crisis	(7) Worry About Health Crisis	(8) Worry About Health Crisis	(9) Worry About Health Crisis
In Linear Group	0.141*	0.258*	0.327**	0.0833*	0.161*	0.161*	0.0900*	0.135*	0.130*
	(0.0806)	(0.153)	(0.157)	(0.0478)	(0.0905)	(0.0920)	(0.0470)	(0.0697)	(0.0695)
COVID-19 News Checking		0.500***	0.434***		0.243***	0.239***		0.179***	0.170***
		(0.0442)	(0.0465)		(0.0260)	(0.0267)		(0.0217)	(0.0217)
Male		-0.806***	-0.654***		-0.437***	-0.382***		-0.362***	-0.308***
		(0.0906)	(0.0934)		(0.0535)	(0.0545)		(0.0442)	(0.0434)
Understanding Q.1: Real Data		-0.00425	0.00558		0.0102	0.00885		0.00256	0.00592
		(0.104)	(0.107)		(0.0619)	(0.0625)		(0.0509)	(0.0501)
Confidence in Understanding Q.1		-0.00134	-0.00152		-0.000494	-0.000967		-0.000548	-0.000952
		(0.00356)	(0.00362)		(0.00209)	(0.00210)		(0.00175)	(0.00177)
Understanding Q.2: Hypothetical		-0.137	-0.225		-0.0989	-0.108		-0.0737	-0.0822
		(0.158)	(0.164)		(0.0945)	(0.0959)		(0.0729)	(0.0731)
Confidence in Understanding Q.2		-0.00374	-0.00428		-0.00239	-0.00240		-0.00233	-0.00225
		(0.00362)	(0.00369)		(0.00213)	(0.00215)		(0.00170)	(0.00172)
Accurate Prediction		0.156	0.218		0.155	0.155		0.139	0.134
		(0.186)	(0.192)		(0.109)	(0.110)		(0.102)	(0.0990)
Unreasonable Prediction		0.225	0.325*		0.182*	0.206*		0.143	0.154
		(0.182)	(0.188)		(0.107)	(0.107)		(0.100)	(0.0974)
Confidence in Prediction		0.00622***	0.00579***		0.00322**	0.00304**		0.00226**	0.00207*
		(0.00219)	(0.00223)		(0.00129)	(0.00131)		(0.00110)	(0.00108)
Democrat			0.732***			0.448***			0.356***
			(0.108)			(0.0633)			(0.0505)
Republican			-0.282**			-0.154**			-0.154**
			(0.118)			(0.0685)			(0.0638)
Worry About Economic Crisis			0.707***		0.352***	0.380***		0.295***	0.309***
			(0.0555)		(0.0303)	(0.0307)		(0.0314)	(0.0302)
Live in city with <50K People			0.0156			0.0222			0.0255
			(0.103)			(0.0599)			(0.0495)
Live in city with >500K People			-0.132			-0.0588			-0.0538
			(0.122)			(0.0716)			(0.0586)
Education			-0.0258			-0.0213			-0.0128
			(0.0359)			(0.0210)			(0.0171)
Age			-0.00132			-0.000164			-0.000645
			(0.00336)			(0.00197)			(0.00156)
State of Residence			0.00777**			0.00512**			0.00403**
			(0.00359)			(0.00206)			(0.00161)
Restrictions in the State			-0.156			-0.102			-0.0790
			(0.111)			(0.0658)			(0.0507)
Constant							3.938***	2.336***	2.420***
							(0.0332)	(0.190)	(0.234)
Observations	2074	1837	1828	2074	1837	1828	2074	1837	1828
Adjusted R^2							0.001	0.148	0.197

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.A.6: Determinants of support for keeping shops closed. Coefficients estimated through ordered Logit regressions (Columns 1-3), ordered Probit regressions (Columns 4-6) and Ordinary Least Squares (OLS) regressions (Columns 7-9). Standard errors are reported in parentheses. All coefficients for the control variables are reported.

	(1) Support for Closing Businesses	(2) Support for Closing Businesses	(3) Support for Closing Businesses	(4) Support for Closing Businesses	(5) Support for Closing Businesses	(6) Support for Closing Businesses	(7) Support for Closing Businesses	(8) Support for Closing Businesses	(9) Support for Closing Businesses
In Linear Group	0.0406	-0.378**	-0.424**	0.0251	-0.181*	-0.213**	0.0261	-0.125	-0.121
	(0.0822)	(0.161)	(0.168)	(0.0491)	(0.0934)	(0.0958)	(0.0512)	(0.0880)	(0.0842)
Worry About Health Crisis		0.997***	1.067***		0.550***	0.592***		0.527***	0.543***
		(0.0524)	(0.0567)		(0.0285)	(0.0313)		(0.0291)	(0.0282)
COVID-19 News Checking		0.0288	0.0748		0.0145	0.0387		-0.00802	0.0147
		(0.0461)	(0.0477)		(0.0268)	(0.0277)		(0.0228)	(0.0219)
Male		-0.112	-0.0890		-0.0630	-0.0532		-0.0252	-0.0200
		(0.0956)	(0.0984)		(0.0561)	(0.0574)		(0.0468)	(0.0452)
Understanding Q.1: Real Data		0.131	0.132		0.0560	0.0543		0.0429	0.0319
		(0.109)	(0.111)		(0.0637)	(0.0646)		(0.0550)	(0.0533)
Confidence in Understanding Q.1		0.00955***	0.00842**		0.00457**	0.00406*		0.00393**	0.00337*
		(0.00367)	(0.00371)		(0.00213)	(0.00215)		(0.00198)	(0.00186)
Understanding Q.2: Hypothetical		0.300*	0.348**		0.138	0.168*		0.0909	0.0949
		(0.168)	(0.175)		(0.0974)	(0.0996)		(0.0923)	(0.0882)
Confidence in Understanding Q.2		-0.000421	-0.000228		0.000629	0.000817		-0.000418	-0.000429
		(0.00375)	(0.00379)		(0.00217)	(0.00220)		(0.00202)	(0.00190)
Accurate Prediction		0.480**	0.450**		0.293***	0.262**		0.210**	0.172*
		(0.190)	(0.193)		(0.113)	(0.115)		(0.0979)	(0.0903)
Unreasonable Prediction		0.0871	0.0806		0.0701	0.0529		0.0335	0.0168
		(0.183)	(0.186)		(0.110)	(0.111)		(0.0954)	(0.0884)
Confidence in Prediction		-0.00451*	-0.00426*		-0.00266**	-0.00268*		-0.00251**	-0.00236**
		(0.00234)	(0.00237)		(0.00135)	(0.00138)		(0.00122)	(0.00115)
Democrat			0.545***			0.310***			0.190***
			(0.116)			(0.0673)			(0.0513)
Republican			-0.491***			-0.298***			-0.299***
			(0.120)			(0.0701)			(0.0651)
Worry About Economic Crisis			-0.494***			-0.289***			-0.257***
			(0.0613)			(0.0350)			(0.0265)
Live in city with <50K People			0.0314			0.0310			0.0447
			(0.107)			(0.0625)			(0.0491)
Live in city with >500K People			0.0230			-0.00403			-0.00391
			(0.129)			(0.0748)			(0.0622)
Education			-0.0258			-0.0121			-0.0107
			(0.0379)			(0.0220)			(0.0178)
Age			-0.00105			-0.00115			-0.00126
			(0.00356)			(0.00204)			(0.00172)
State of Residence			0.00274			0.00158			0.000767
			(0.00367)			(0.00217)			(0.00152)
Restrictions in the State			-0.0175			-0.00715			-0.000582
			(0.117)			(0.0688)			(0.0521)
Constant							4.067***	1.804***	2.901***
							(0.0356)	(0.183)	(0.240)
Observations	2074	1837	1828	2074	1837	1828	2074	1837	1828
Adjusted R^2							-0.000	0.233	0.304

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.A.7: Determinants for suggested reopening day. Columns 1-3 report coefficients obtained through Ordinary Least Squares (OLS) regressions, Columns 3-6 report coefficients obtained through Logit regressions (on the months before reopening) and Columns 7-9 report coefficients from OLS regressions (on the months before reopening). Standard errors are reported in parentheses. All coefficients for the control variables are reported.

	(1) Days Until Reopening Businesses	(2) Days Until Reopening Businesses	(3) Days Until Reopening Businesses	(4) Months until reopening	(5) Months until reopening	(6) Months until reopening	(7) Months until reopening	(8) Months until reopening	(9) Months until reopening
In Linear Group	2.295	17.38**	14.65**	0.150*	0.396**	0.335*	3.044	18.60***	16.00**
	(3.133)	(7.069)	(7.010)	(0.0790)	(0.174)	(0.175)	(3.054)	(6.843)	(6.804)
Worry About Health Crisis		12.45***	13.14***		0.682***	0.701***		11.43***	11.94***
		(1.789)	(1.910)		(0.0523)	(0.0548)		(1.729)	(1.858)
COVID-19 News Checking		3.071*	3.932**		0.0710*	0.120***		3.296**	4.147**
		(1.609)	(1.664)		(0.0420)	(0.0430)		(1.567)	(1.624)
Male		10.53***	9.169***		0.351***	0.340***		11.20***	10.07***
		(3.377)	(3.335)		(0.0893)	(0.0889)		(3.305)	(3.267)
Understanding Q.1: Real Data		-1.236	-0.517		-0.0111	0.0113		-1.394	-0.663
		(4.088)	(4.112)		(0.104)	(0.105)		(3.996)	(4.027)
Confidence in Understanding Q.1		0.109	0.0996		0.00595*	0.00528		0.0937	0.0862
		(0.128)	(0.129)		(0.00352)	(0.00360)		(0.122)	(0.123)
Understanding Q.2: Hypothetical		-18.05**	-15.87**		-0.353*	-0.309*		-18.06***	-16.04**
		(7.177)	(7.125)		(0.181)	(0.183)		(6.976)	(6.941)
Confidence in Understanding Q.2		-0.310**	-0.299**		-0.00709*	-0.00716*		-0.296**	-0.285**
		(0.138)	(0.139)		(0.00363)	(0.00375)		(0.130)	(0.132)
Accurate Prediction		10.58*	9.343		0.368**	0.337**		10.95*	9.881
		(6.297)	(6.295)		(0.165)	(0.161)		(6.155)	(6.164)
Unreasonable Prediction		6.590	4.787		0.0971	0.0854		6.706	5.081
		(6.060)	(6.071)		(0.160)	(0.157)		(5.930)	(5.953)
Confidence in Prediction		0.216***	0.205**		0.0000901	-0.000193		0.211***	0.198**
		(0.0799)	(0.0811)		(0.00205)	(0.00207)		(0.0782)	(0.0794)
In Linear Group			0						
			(.)						
Democrat			0.107			0.186*			1.055
			(3.683)			(0.102)			(3.592)
Republican			1.912			-0.316**			3.064
			(4.675)			(0.125)			(4.573)
Worry About Economic Crisis			-3.597*			-0.233***			-2.972
			(1.981)			(0.0520)			(1.923)
Live in city with <50K People			6.259*			0.140			5.503
			(3.626)			(0.0976)			(3.565)
Live in city with >500K People			9.164**			0.184			7.363*
			(4.394)			(0.113)			(4.271)
Education			-1.798			-0.0753**			-1.894
			(1.319)			(0.0341)			(1.282)
Age			-0.151			-0.00831**			-0.153
			(0.116)			(0.00327)			(0.113)
State of Residence			-0.00686			0.000271			0.00475
			(0.127)			(0.00298)			(0.127)
Restrictions in the State			-1.382			-0.00498			-0.420
			(4.178)			(0.110)			(4.126)
In Linear Group						0			
						(.)			
In Linear Group									0
									(.)
Constant	65.38***	-0.312	24.09				54.48***	-7.962	12.68
	(2.156)	(11.67)	(16.94)				(2.105)	(11.39)	(16.53)
Observations	2061	1828	1819	2074	1837	1828	2074	1837	1828
Adjusted R^2	-0.000	0.055	0.056				-0.000	0.053	0.053

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.A.8: Determinants of support for a tax to finance masks' distribution. The coefficients are estimated through ordered Logit regressions (Columns 1-3), ordered Probit regressions (Columns 4-6) and ordinary least squares (OLS) regressions (Columns 7-9). Standard errors are reported in parentheses. All coefficients for the control variables are reported.

	(1) Support for Mask-Buying Tax	(2) Support for Mask-Buying Tax	(3) Support for Mask-Buying Tax	(4) Support for Mask-Buying Tax	(5) Support for Mask-Buying Tax	(6) Support for Mask-Buying Tax	(7) Support for Mask-Buying Tax	(8) Support for Mask-Buying Tax	(9) Support for Mask-Buying Tax
In Linear Group	-0.0218	0.307**	0.305**	-0.00837	0.163*	0.156*	-0.0130	0.175*	0.162
	(0.0781)	(0.151)	(0.153)	(0.0465)	(0.0882)	(0.0892)	(0.0608)	(0.103)	(0.103)
Worry About Health Crisis		0.481***	0.471***		0.280***	0.276***		0.307***	0.295***
		(0.0506)	(0.0538)		(0.0294)	(0.0313)		(0.0335)	(0.0346)
Likelihood to Wear Masks		0.648***	0.617***		0.376***	0.362***		0.410***	0.386***
		(0.0496)	(0.0504)		(0.0288)	(0.0294)		(0.0304)	(0.0305)
COVID-19 News Checking		0.0403	0.0682		0.0213	0.0384		0.0184	0.0393
		(0.0423)	(0.0434)		(0.0249)	(0.0255)		(0.0278)	(0.0282)
Male		0.0372	0.0455		0.0198	0.0280		0.0208	0.0284
		(0.0883)	(0.0896)		(0.0523)	(0.0530)		(0.0582)	(0.0576)
Understanding Q.1: Real Data		0.152	0.169*		0.0865	0.0912		0.0818	0.0886
		(0.101)	(0.102)		(0.0597)	(0.0601)		(0.0672)	(0.0665)
Confidence in Understanding Q.1		0.00648*	0.00602*		0.00343*	0.00287		0.00241	0.00181
		(0.00352)	(0.00353)		(0.00205)	(0.00205)		(0.00241)	(0.00239)
Understanding Q.2: Hypothetical		-0.454***	-0.452***		-0.247***	-0.239**		-0.273**	-0.258**
		(0.157)	(0.159)		(0.0917)	(0.0927)		(0.108)	(0.107)
Confidence in Understanding Q.2		-0.0108***	-0.0112***		-0.00577***	-0.00583***		-0.00543**	-0.00546**
		(0.00362)	(0.00364)		(0.00209)	(0.00210)		(0.00253)	(0.00252)
Accurate Prediction		0.186	0.141		0.0999	0.0782		0.129	0.103
		(0.184)	(0.185)		(0.107)	(0.108)		(0.127)	(0.125)
Unreasonable Prediction		0.165	0.147		0.0870	0.0792		0.114	0.106
		(0.179)	(0.180)		(0.104)	(0.105)		(0.123)	(0.122)
Confidence in Prediction		0.00675***	0.00734***		0.00345***	0.00367***		0.00423***	0.00435***
		(0.00217)	(0.00220)		(0.00126)	(0.00127)		(0.00148)	(0.00146)
Democrat			0.378***			0.216***			0.250***
			(0.104)			(0.0612)			(0.0694)
Republican			-0.261**			-0.151**			-0.188**
			(0.116)			(0.0683)			(0.0755)
Worry About Economic Crisis			-0.0979*			-0.0676**			-0.0791**
			(0.0538)			(0.0315)			(0.0349)
Live in city with <50K People			0.115			0.0759			0.0974
			(0.0983)			(0.0580)			(0.0640)
Live in city with >500K People			0.0488			0.0397			0.0531
			(0.119)			(0.0697)			(0.0773)
Education			-0.0209			-0.0176			-0.0238
			(0.0345)			(0.0204)			(0.0220)
Age			-0.00942***			-0.00582***			-0.00748***
			(0.00325)			(0.00191)			(0.00214)
State of Residence			-0.00313			-0.00186			-0.00270
			(0.00341)			(0.00197)			(0.00227)
Restrictions in the State			-0.122			-0.0561			-0.0612
			(0.108)			(0.0640)			(0.0701)
Constant							3.251***	0.176	1.101***
							(0.0421)	(0.214)	(0.310)
Observations	2072	1834	1825	2072	1834	1825	2072	1834	1825
Adjusted R^2							-0.000	0.230	0.258

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.A.9: Determinants of likelihood to wear a mask when going out if provided with one. The coefficients are estimated through ordered Logit regressions (Columns 1-3), ordered Probit regressions (Columns 4-6) and Ordinary Least Squares (OLS) regressions (Columns 7-9). Standard errors are reported in parentheses. All coefficients for the control variables are reported

	(1) Likelihood Wear Masks	(2) Likelihood Wear Masks	(3) Likelihood Wear Masks	(4) Likelihood Wear Masks	(5) Likelihood Wear Masks	(6) Likelihood Wear Masks	(7) Likelihood Wear Masks	(8) Likelihood Wear Masks	(9) Likelihood Wear Masks
In Linear Group	0.00311	-0.314**	-0.350**	0.00492	-0.195**	-0.209**	0.00611	-0.150**	-0.161**
	(0.0818)	(0.157)	(0.160)	(0.0488)	(0.0929)	(0.0942)	(0.0482)	(0.0694)	(0.0703)
Worry About Health Crisis		0.907***	0.908***		0.512***	0.511***		0.467***	0.463***
		(0.0514)	(0.0547)		(0.0281)	(0.0301)		(0.0284)	(0.0292)
COVID-19 News Checking		0.138***	0.129***		0.0840***	0.0794***		0.0450**	0.0422**
		(0.0458)	(0.0472)		(0.0266)	(0.0274)		(0.0212)	(0.0212)
Male		-0.255***	-0.270***		-0.151***	-0.163***		-0.0940**	-0.105**
		(0.0944)	(0.0963)		(0.0555)	(0.0564)		(0.0435)	(0.0434)
Understanding Q.1: Real Data		0.0281	0.0136		0.0238	0.0116		0.0126	0.00199
		(0.109)	(0.110)		(0.0637)	(0.0643)		(0.0512)	(0.0509)
Confidence in Understanding Q.1		0.00571	0.00493		0.00338	0.00305		0.00309	0.00293
		(0.00372)	(0.00378)		(0.00211)	(0.00213)		(0.00198)	(0.00194)
Understanding Q.2: Hypothetical		0.189	0.237		0.111	0.132		0.0930	0.111
		(0.164)	(0.167)		(0.0971)	(0.0984)		(0.0741)	(0.0747)
Confidence in Understanding Q.2		0.00250	0.00272		0.00164	0.00161		0.000816	0.000547
		(0.00380)	(0.00384)		(0.00216)	(0.00217)		(0.00200)	(0.00196)
Accurate Prediction		0.435**	0.431**		0.249**	0.236**		0.179*	0.163*
		(0.187)	(0.188)		(0.110)	(0.110)		(0.0975)	(0.0957)
Unreasonable Prediction		0.497***	0.493***		0.279***	0.268**		0.181*	0.165*
		(0.183)	(0.184)		(0.107)	(0.108)		(0.0952)	(0.0938)
Confidence in Prediction		0.00211	0.00276		0.00147	0.00173		0.000839	0.00103
		(0.00227)	(0.00230)		(0.00133)	(0.00135)		(0.00111)	(0.00109)
Democrat			0.161			0.104			0.0644
			(0.113)			(0.0659)			(0.0503)
Republican			-0.384***			-0.208***			-0.175***
			(0.121)			(0.0704)			(0.0616)
Worry About Economic Crisis			-0.132**			-0.0799**			-0.0898***
			(0.0573)			(0.0330)			(0.0277)
Live in city with <50K People			0.0832			0.0430			0.0391
			(0.104)			(0.0610)			(0.0497)
Live in city with >500K People			0.588***			0.339***			0.242***
			(0.129)			(0.0750)			(0.0559)
Education			-0.0767**			-0.0355			-0.0144
			(0.0374)			(0.0216)			(0.0178)
Age			0.00713**			0.00425**			0.00282*
			(0.00350)			(0.00204)			(0.00153)
State of Residence			0.0170***			0.0102***			0.00640***
			(0.00395)			(0.00225)			(0.00136)
Restrictions in the State			-0.154			-0.0974			-0.0853
			(0.114)			(0.0672)			(0.0565)
Constant							4.090***	1.651***	2.130***
							(0.0335)	(0.189)	(0.254)
Observations	2072	1835	1826	2072	1835	1826	2072	1835	1826
Adjusted R^2							-0.000	0.227	0.255

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.A.10: Survey Questions - Part I

Page	Worry, Policy and Attitudinal Questions	Figure Shown
1	Respondents are shown a graph that shows data on deaths from COVID-19 on either a linear scale or a logarithmic scale. Below the figure we provide information on how to read the scale and on the total number of deaths as of April 18th 2020	Figure 1 - Group A linear scale and Group B logarithmic scale
2	How worried are you about the health and economic crises caused by the coronavirus pandemic?	None
2a	How worried are you about the HEALTH crisis in the US? Rate your level of worry from 1 (Not worried at all) to 5 (Extremely worried)	None
2b	How worried are you about the ECONOMIC crisis in the US? Rate your level of worry from 1 (Not worried at all) to 5 (Extremely worried)	None
3	Do you agree that all NON-ESSENTIAL businesses should be closed? Essential businesses are supermarkets, pharmacies, etc. (Strongly Disagree - Strongly Agree)	None
4	Until when do you think non-essential businesses should closed? Please insert a date below. (Month, Day)	None
5a	It has been suggested that governments should send protective masks to their citizens. If the government sent you a supply of masks, how often would you wear them when you go outside? (Never - Always)	None
5b	How strongly would you support a tax that finances the distribution of masks for everyone in your state? (Strongly oppose - Strongly support)	None

Table 3.A.11: Survey Questions

Page	Understanding Questions	Figure Shown
6a	In this question we encourage you to give your best guess. Approximately, how many TOTAL DEATHS do you think there will be by on April 25th 2020? Please insert a NUMBER below:	Figure 1 - Group A linear scale and Group B logarithmic scale
6b	How confident do you feel in your answer? (1-100%)	Figure 1 - Group A linear scale and Group B logarithmic scale
7a	Looking at this figure, did the total number of deaths increase MORE between March 31st and April 6th or between April 6th and April 12th? (It increased more between March 31st and April 6th; It increased more between 6th and April 12th; The number of new cases was the same in the two weeks, I don't know)	Figure 1 - Group A linear scale and Group B logarithmic scale
7b	How confident do you feel in your answer? (1-100	Figure 1 - Group A linear scale and Group B logarithmic scale
8a	When was there a LARGER DIFFERENCE between the number of men and women dying after suffering infection Type Z? (From week 2 to week 3, From week 5 to week 6, From week 9 to week 10, From week 13 to week 14, I do not know)	Figure from Okan (2016)
8b	How confident do you feel in your answer? (1-100	Figure from Okan (2016)

Table 3.A.12: Survey Questions - Part III

Page	Demographics	Figure Shown
9	How often do you read the news about the coronavirus pandemic? Please give us your best guess. (Less than once a day - Five or more times a day)	None
10	In which state do you currently reside? (Choice from menu)	None
11	How many people live in your town/city? (Less than 50,000; Between 50,000 and 500,000; More than 500,000; I don't know)	None
12	What is your year of birth? (Free answer)	None
13	What is the highest level of school you have completed or the highest degree you have received? (Choice from type of degree list)	None
14	What is your gender? (Male, Female, Other, Prefer not to declare)	None
15	Information about your income is very important for us to analyze data. Would you please give your best guess? Please indicate the answer that includes your entire household income in 2019 before taxes. (Choice between income brackets)	None
16	Generally speaking, do you usually think of yourself as a Republican, a Democrat, an Independent, or something else? (Republican, Democrat, Independent, Other, No preference)	None
17	Which device did you use to complete this survey? (I used a laptop or a desktop computer, I used a smartphone, I used a tablet, Other)	None

Chapter 4

Covid-19 Vaccine Passport and International Travelling: The Combined Effect of Two Nudges on Americans' Support for the Pass

4.1 Introduction

The coronavirus disease 2019 (Covid-19) pandemic has caused catastrophic losses both in terms of human lives (WHO, 2021) and to the economy (McKibbin and Fernando, 2020; Cutler and Summers, 2020). Some of the sectors that were hit more dramatically are those connected with international travelling. For instance, the tourism sector and the airline industry have been brought to their knees by the many travelling restrictions adopted worldwide (Gössling et al., 2020), and by the obvious reluctance of many to travel during a pandemic (Immordino et al., 2021). According to The World Travel and Tourism Council, in 2020 the travel and tourism sector experienced staggering losses for $3.8 trillions (Schengenvisainfo, 2021). Moreover, a new report of the UN's Air Transportation Agency indicates that Covid-19 caused a decline in international air travel of around 60%, which resulted in losses for over $370 billion to the airline industry (UN News, 2021). However, as existing vaccines have proven to be safe and effective (Prüβ, 2021; Haas et al., 2021), these key industries are looking forward to better times, especially in light of the possible introduction of Covid-19 vaccine passports (hereinafter, Covid passes). Covid-19 passes allow the bearer to show information on their immunisation status and permit people who have vaccinated against Covid-19, or have recently recovered from the virus, to face fewer restrictions while travelling.

While Covid passes present significant ethical and scientific challenges (Hall and Studdert, 2021), requiring proof of vaccination for international travelling is not a new practice. For instance, the World Health Organization (WHO) has long endorsed certificates confirming vaccination against yellow fever to travel to certain countries (UN News, 2013). Building on this precedent, policymakers and private companies have either introduced, or are planning to introduce, some form of Covid pass for international travelling. For example, the European Commission has reached an agreement on the "Digital Covid Certificate", which will provide a proof that a person has been vaccinated against Covid-19, received a negative test result, or recently recovered from Covid-19 (European Commission, 2021). Moreover, leading airlines are working on the IATA Travel Pass App and are considering allowing only holders of such pass to board their flights (IATA, 2021a).

In order to be successful, Covid passes need to be widely supported by the public. From this perspective, the demise of Contact Tracing Apps is a case in point (Rowe et al., 2020), showing that even the most promising and hyped technological innovation can fail to deliver if it is perceived negatively by potential adopters. In a similar vein, if Covid passes are implemented without the support of the general public they might lead to significant problems like lowering vaccine uptake (NBC, 2021). Luckily, at least for international travelling, Covid passes seem to be perceived somewhat favourably among the general public. A recent survey carried out in the U.S. reveals that only about one third of Americans is against requiring proof of vaccination for international travelling in the form of a Covid pass (YouGov America, 2021), while in a study carried out by IATA 80% of respondents stated that they intend to use the IATA Travel Pass App as soon as it becomes available (IATA, 2021b).

Due to their enormous potential impact, Covid passes have been hotly discussed in the academic literature (Osama et al., 2021; Memish et al., 2021; Tanner and Flood, 2021; Pavli and Maltezou, 2021). However, all existing studies have been purely qualitative or observational (Drury et al., 2021), with one notable exception (Guidi et al., 2021). Recent research related to Covid-19 has shown that behavioural interventions can have a significant impact on people's perception of the pandemic and foster people's preventive and pro-social behaviours (Romano, Sotis et al., 2020; Pennycook et al., 2020; Kim et al., 2020; Milkman et al., 2021; Ceylan and Hayran, 2021). This literature has shown that experimental studies can offer precious guidance to policymakers and companies. This paper expands this literature and offers guidance on how to increase the support for a Covid pass through a communication campaign based on nudging.

In particular, we present the results from a double blind randomised online experiment with a sample of $N = 4000$ Americans to test whether: *i*) two nudges can increase the level of support for a Covid pass for international travelling; *ii*) there are synergies between the effects of the two nudges; and *iii*) these nudges generate negative spillovers on intentions to get vaccinated.

The first nudge exploits the status quo bias, which is an effective technique to increase the acceptance of a policy by presenting it as a sign of continuity with the past, and has proven effective in a variety of contexts (Samuelson and Zeckhauser, 1988). Here, we flag that proof of vaccination for international travelling is not a novel idea, and hypothesise that this will increase the support for the Covid pass. The second nudge, instead, builds on peer effects. There is evidence that the information on peers' actions can induce pro-social behaviours (Allcott, 2011; Ayres et al., 2013), and that people tend to conform to the policy preferences of their peers (Rothschild and Malhotra, 2014). Moreover, previous literature has shown a tendency to conform driven by a need to belong to a group, and the influence that the group's opinion has on the individual (Fiske, 2018; Deutsch and Gerard, 1955). In this vein, we hypothesise that informing respondents about the limited opposition to Covid passes for international travelling would increase the support for this policy.

4.2 Background Literature and Theoretical Framework

Nudges are now widely accepted as an effective tool to influence behaviours without constraining individuals' ability to choose (Sunstein, 2015; Loewenstein and Chater, 2017; Romano and Sotis, 2021). Recent studies have shown that nudges are effective even in the context of Covid to promote pro-social behaviours (Pennycook et al., 2020; Kim et al., 2020; Milkman et al., 2021). Here, we investigate whether they can also be used to increase the support for the Covid pass.

4.2.1 Status Quo Bias

The first nudge on which we rely is the status quo bias. The basic idea is that people are more likely to support a policy if it is perceived as a continuation of the past. In other words, whenever "an advertiser, political actor, or any other persuader wishes to make a practice or product acceptable, framing their preferred alternative as the status quo is likely to enhance its position and increase its support" (Crandall et al., 2009). For instance, a recent study shows that support for carbon mitigation policies is higher if they are presented as a continuation of the status quo (Lang et al., 2021). Similar results are obtained even for practices as controversial as torture. Crandall et al. (2009) observe that when torture is presented as a longstanding practice it is perceived as more justifiable and effective. Scholars have advanced a wide array of explanations for the existence of this bias ranging from loss aversion and regret avoidance to repeated exposure (Eidelman and Crandall, 2012). However, there is evidence that the bias also stems from people's assumption of goodness associated with the mere existence and longevity of a given state of the world (Eidelman and Crandall, 2012). Against this background, it is reasonable to expect that the status quo bias can be exploited in connection with the Covid pass. In particular, flagging that requiring proof of vaccination for international travelling is not unprecedented should trigger the status quo bias, and hence increase the support for the Covid pass.

4.2.2 Peer Effects

The second nudge we test is peer effects. Several studies found that social norms and peer influence can shape behaviours and attitudes (Allcott, 2011; Ayres et al., 2013). In a similar vein, other studies find that polls results can influence individual level attitudes, triggering the so-called "bandwagon effect" (Rothschild and Malhotra, 2014). When polls indicate that a policy is widely supported, even more people will be persuaded to support that policy (Hardmeier, 2008). Thus, polls not only describe public opinion, but can also influence it. In fact, in many democratic countries there are restrictions on carrying out and publishing polls before the elections (Barnfield, 2020). In the context of policy support, the bandwagon effect causes an increase in support for a given policy motivated by the popularity of the policy itself. As the Covid pass for international travelling already shows a relatively good level of support among segments of the public, we attempt to leverage the bandwagon effect to further increase the support for the pass.

4.2.3 Interaction Among Nudges

Policymakers are increasingly relying on nudges to promote certain behaviours. Therefore, a key question is how multiple nudges targeted at promoting a given behaviour interact. Consider the case in which nudges A and B are both effective in fostering behaviour X. What happens when they are used simultaneously on the same target behaviour?

As indicated in Figure 4.1, the interaction between two nudges can: *i*) be synergistic, when their joint effect is larger than the sum of the effects of each nudge separately, *ii*) be weakly additive, when their joint effect is larger than the effect of each of the two nudges when used separately, but smaller than their sum *iii*) backfire, when the two nudges together produce a smaller effect than either of the two nudges used alone. Understanding the kind of interaction between nudges is extremely important, as policymakers generally

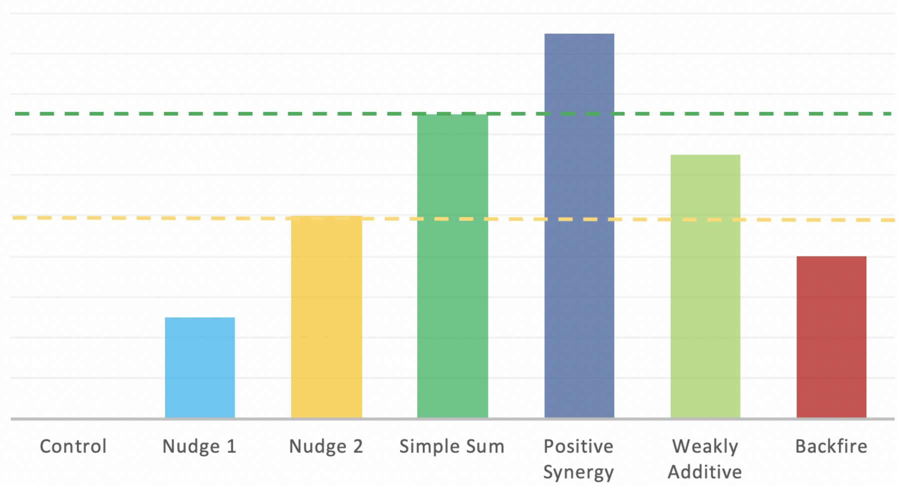

Figure 4.1: Possible interactions among nudges

employ a portfolio of tools and nudges to achieve a given goal (Drews et al., 2020). The evidence produced by the literature is, however, very limited. A recent study focused on the interaction between a moral suasion nudge aimed at reducing electricity consumption during peak load events and peer effect comparison targeting aggregate household electricity consumption (Brandon et al., 2019). The study identified a synergistic relationship between the two nudges.

A related nascent literature has attempted to identify the relationship between price incentives and nudges (Drews et al., 2020). The handful of works carried out in this domain have produced conflicting evidence (Hilton et al., 2014; Schall et al., 2016; Panzone et al., 2018). A recent survey on the issue concluded that due to the very small number of works on this area "our understanding [...] is limited, as studies rarely use an approach that allows properly assessing synergy or the causes and mechanisms of it". (Drews et al., 2020). One hypothesis that has been advanced is that there might be diminishing marginal returns from policy pressure, and therefore the relationship among nudges might depend on the level of support for a given policy (Brandon et al., 2019; Drews et al., 2020). Thus, for example, two nudges might be in a synergistic relationship when a policy has a low level of support, but then change the interaction to weakly additive when the support for the policy grows beyond a certain threshold.

We attempt to contribute to this nascent and important field of research on nudges interactions by investigating the relationship between two widely adopted nudges in a highly salient domain.

4.2.4 Behavioural Spillovers

Another important question is whether a nudge has significant spillovers that affect other activities. That is, if nudge A, intended to promote behaviour X, also affects behaviour Y. The literature has found evidence of both positive and negative spillovers in different domains. For instance, a study found a strong interdependence between fuel-efficient driving styles and willingness to reduce meat consumption (Van der Werff et al., 2013). One reason behind positive spillovers of this kind might be that people wish to perceive themselves (and to be perceived) as consistent, and hence attempt to act in a consistent manner across different domains. In this vein, if they engage in the pro-environmental behaviour X, they are more likely to engage in the pro-environmental behaviour Y (Cialdini et al., 1995). Instead, in other cases scholars have observed negative spillovers. For example, a study observed that the owners of electric cars felt less compelled to engage in pro-environmental behaviour than owners of traditional cars (Klöckner et al., 2013). One of the possible causes of negative spillovers is the so-called moral-licensing effect. If people feel that they have done their part, they are more likely to engage in negative behaviours.

Understanding the sign of the spillovers is crucial, because in presence of negative spillovers nudges that appear to be effective might backfire by triggering a negative response on other behaviours. Scholars are therefore trying to devise experiments that investigate the existence of such spillovers and their sign. However, the debate is still ongoing and most studies so far have focused on pro-environmental behaviours. Understanding whether there are spillovers from the introduction of Covid passes and their direction should be a key priority for policymakers. For instance, if promoting the Covid pass results in lower vaccination uptake, governments should be very careful before implementing this tool.

4.3 Materials and Methods

We recruited a sample of $N = 4000$ Americans on Prolific.co. To be eligible, people had to be at least 18 years of age and be resident in the U.S.. Participants took on average approximately 5 minutes and a half to complete the survey, and they were paid \$0.55. The data collection started and finished on the 15th of May 2021. We obtained informed consent from all participants prior to the beginning of the online survey, which was approved by the faculty ethics committees of Yale University, Bocconi University and the London School of Economics.

To begin with, we asked respondents about their vaccination status, which allowed us to

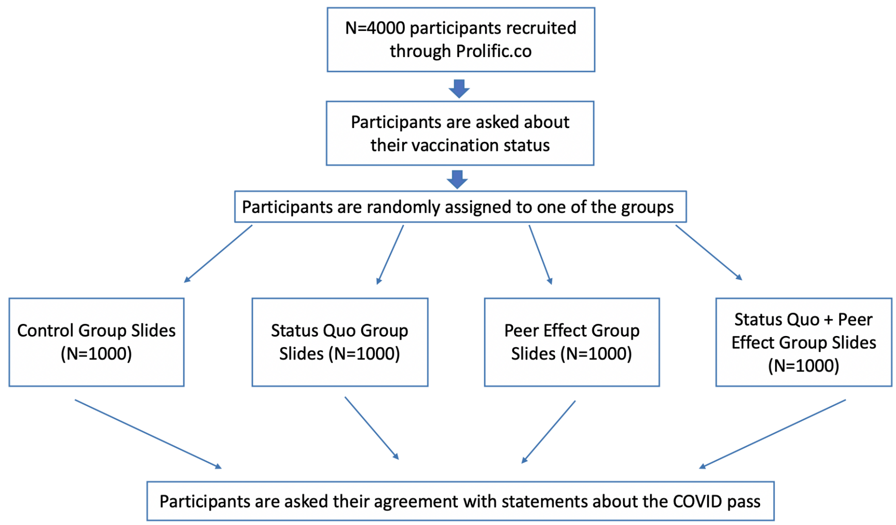

Figure 4.2: Experiment Flow

distinguish between respondents who completed their vaccination schedule and those who are still waiting for their first or second dose. Moreover, we asked respondents who have not yet completed their cycle whether they intend to complete their cycle or not. In the same vein, we asked respondents who have not received a vaccine whether they intend to get vaccinated when they will have the opportunity.

After this, respondents were randomly assigned to one of four different groups: Control, Status Quo, Peer Effects and Status Quo + Peer Effects (Figure 4.2).

The respondents in the Control Group only received basic information on the features and the purpose of a Covid pass for international travelling. The respondents included in the Status Quo condition were also informed that requiring proof of vaccination for international travelling is not unprecedented. Moreover, they were shown a picture of the International Certificate of Vaccination or Prophylaxis, or more simply the Yellow Card, endorsed by the World Health Organization to allow travellers to show proof of vaccination against yellow fever when entering certain countries. Finally, respondents in the Peer Effects condition were informed that according to a recent survey by YouGov and the Economist only one third of Americans oppose a Covid pass for international travelling. Last, respondents in the Status Quo + Peer Effects condition were informed about both the fact that requiring proof of vaccination is not a novel idea, and that only one third of Americans oppose a Covid pass for international travelling (see Figure 4.3).

After seeing the treatment, respondents were asked to state their level of agreements on a scale from zero to ten with statements intended to capture their support for the Covid

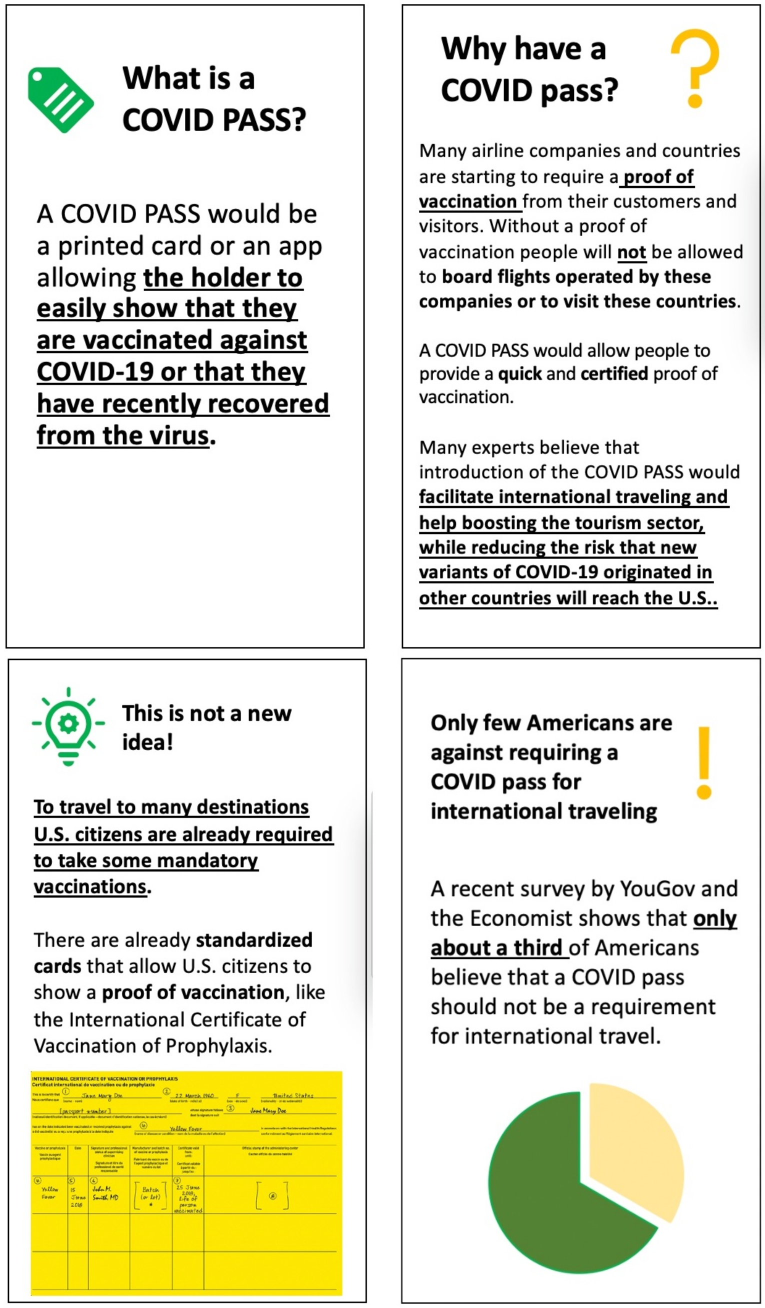

Figure 4.3: The top slides are shown to all participants. Respondents in the Control Group only see the top slides. Respondents in the Status Quo Group also see the bottom left slide. Respondents in the Peer Effects Group also see the bottom right slide. Respondents in the Status Quo + Peer Effects Group see all four slides.

pass. The first three statements aim at capturing the perceived importance of the Covid pass. Statements 4-8 intend to capture the perceived unfairness of the Covid pass along various dimensions. Statements 9 and 10 target additional concerns connected with the Covid pass, namely whether it can be forged and how it would affect vaccination rates. Statement 11 asks respondents whether they think that only people with a Covid pass should be allowed to board international flights. Statement 12 deals with the troublesome finding of the literature that some people might intentionally get infected with Covid-19 if a Covid pass is introduced (Garrett et al., 2021), while statement 13 intends to capture the overall perceived balance among pros and cons of the Covid pass. Table 4.2 reports the full list of statements, their number and the summary statistics (mean and standard deviation). The number of the statements conveys the order in which they were asked, and will be used to denote the statements throughout the article.

Moreover, we asked respondents how likely they were to get vaccinated if a Covid pass for international travelling is introduced. The precise wording of the question depends on the vaccination status declared by the respondents at the begin of the survey. Therefore, for instance, respondents who have received only one dose are asked if they want to complete their vaccination cycle if the Covid pass is introduced. Instead, respondents who have not received any dose are asked if they intend to get vaccinated if a Covid pass is introduced. The answers are presented on a five-point Likert scale ranging from "Very unlikely" to "Very likely".

Last, we asked a series of questions that are used as controls. Such questions capture the level of trust in key institutions like the Federal Government, the respondent's State Government and the Centers for Disease Control and Prevention (CDC) or in pharmaceutical companies and tech giants. Respondents also faced an attention check towards the end of the questionnaire. In the attention check respondents received a multiple choice question in which they were asked to select the answer "5" if they were paying attention. The results we present in the next section exclude from the analysis the five participants who did not pass the attention check. However, the results remain robust even including these participants. We concluded the survey by asking standard demographic questions like age, education, political affiliation, etc.

4.4 Results

In this section we present the results of our experiment for each statement individually. In the Appendix, we present the results in a more concise form using factor analysis, grouping all the statements capturing the respondents' support for the pass. The two approaches produce consistent results.

	Group														
	Control			**Status Quo**			**Peer Effect**			**PE + Status Quo**			**Total**		
	No.	Col %	Cum %	No.	Col %	Cum %	No.	Col %	Cum %	No.	Col %	Cum %	No.	Col %	Cum %
Political Orientation															
Republican	167	16.7	16.7	165	16.5	16.5	163	16.3	16.3	163	16.4	16.4	658	16.5	16.5
Democrat	571	57.2	73.9	575	57.5	74.0	573	57.4	73.7	550	55.3	71.7	2269	56.8	73.3
Other or No Strong Preference	261	26.1	100.0	260	26.0	100.0	263	26.3	100.0	282	28.3	100.0	1066	26.7	100.0
Total	999	100.0		1000	100.0		999	100.0		995	100.0		3993	100.0	
Gender															
Other/Prefer not to declare	32	3.2	3.2	20	2.0	2.0	30	3.0	3.0	23	2.3	2.3	105	2.6	2.6
Female	551	55.2	58.4	582	58.2	60.2	607	60.8	63.8	553	55.6	57.9	2293	57.4	60.1
Male	416	41.6	100.0	398	39.8	100.0	362	36.2	100.0	419	42.1	100.0	1595	39.9	100.0
Income															
Less than $10,000	56	5.6	5.6	53	5.3	5.3	66	6.6	6.6	62	6.2	6.2	237	5.9	5.9
$10,000 to $19,999	63	6.3	11.9	64	6.4	11.7	62	6.2	12.8	87	8.8	15.0	276	6.9	12.9
$20,000 to $29,999	93	9.3	21.2	85	8.5	20.2	104	10.4	23.3	82	8.3	23.3	364	9.1	22.0
$30,000 to $39,999	81	8.1	29.4	99	9.9	30.1	95	9.5	32.8	96	9.7	32.9	371	9.3	31.3
$40,000 to $49,999	106	10.6	40.0	106	10.6	40.7	82	8.2	41.0	71	7.2	40.1	365	9.2	40.5
$50,000 to $59,999	112	11.2	51.2	111	11.1	51.9	93	9.3	50.4	82	8.3	48.3	398	10.0	50.4
$60,000 to $69,999	74	7.4	58.6	76	7.6	59.5	81	8.1	58.5	82	8.3	56.6	313	7.9	58.3
$70,000 to $79,999	85	8.5	67.1	66	6.6	66.1	75	7.5	66.0	90	9.1	65.7	316	7.9	66.2
$80,000 to $89,999	42	4.2	71.3	55	5.5	71.6	46	4.6	70.6	58	5.8	71.5	201	5.0	71.3
$80,000 to $89,999	54	5.4	76.8	57	5.7	77.3	55	5.5	76.1	53	5.3	76.8	219	5.5	76.7
$90,000 to $99,999	155	15.5	92.3	142	14.2	91.5	139	13.9	90.1	151	15.2	92.0	587	14.7	91.5
$150,000 or more	77	7.7	100.0	85	8.5	100.0	99	9.9	100.0	79	8.0	100.0	340	8.5	100.0
Education															
Less than high school degree	8	0.8	0.8	7	0.7	0.7	14	1.4	1.4	7	0.7	0.7	36	0.9	0.9
High school graduate (diploma or equivalent)	103	10.3	11.1	104	10.4	11.1	102	10.2	11.6	109	11.0	11.7	418	10.5	11.4
Some college but no degree	206	20.6	31.7	230	23.0	34.1	230	23.0	34.6	227	22.8	34.5	893	22.4	33.8
Associate degree in college (2-year)	93	9.3	41.0	84	8.4	42.5	109	10.9	45.5	111	11.2	45.7	397	9.9	43.7
Bachelor's degree in college	400	40.0	81.1	373	37.3	79.9	347	34.7	80.3	371	37.3	83.0	1491	37.4	81.1
Master's degree or Professional Degree (JD, MD)	176	17.6	98.7	177	17.7	97.6	169	16.9	97.2	148	14.9	97.9	670	16.8	97.8
Doctoral degree	13	1.3	100.0	24	2.4	100.0	28	2.8	100.0	21	2.1	100.0	86	2.2	100.0
Age															
18-25 years old	253	25.3	25.3	250	25.0	25.0	218	21.8	21.8	240	24.1	24.1	961	24.1	24.1
26-35 years old	343	34.3	59.7	354	35.4	60.4	358	35.8	57.7	317	31.9	56.0	1372	34.4	58.4
36-45 years old	185	18.5	78.2	179	17.9	78.3	189	18.9	76.6	194	19.5	75.5	747	18.7	77.1
46-55 years old	91	9.1	87.3	109	10.9	89.2	101	10.1	86.7	108	10.9	86.3	409	10.2	87.4
56-65 years old	64	6.4	93.7	50	5.0	94.2	61	6.1	92.8	73	7.3	93.7	248	6.2	93.6
66-75 years old	21	2.1	95.8	19	1.9	96.1	24	2.4	95.2	31	3.1	96.8	95	2.4	96.0
>75 years old	42	4.2	100.0	39	3.9	100.0	48	4.8	100.0	32	3.2	100.0	161	4.0	100.0
In full or part time employment	659	66.0	100.0	642	64.2	100.0	649	65.0	100.0	643	64.6	100.0	2593	64.9	100.0
Student	106	10.6	100.0	117	11.7	100.0	127	12.7	100.0	120	12.1	100.0	470	11.8	100.0
White	741	74.2	100.0	761	76.1	100.0	730	73.1	100.0	709	71.3	100.0	2941	73.7	100.0

Table 4.1: Sample balance: the frequency table reports the Number, Percentage and Cumulative Percentage of respondents for the following variables: Political Orientation, Gender, Income, Education, Age, Employment and Race. Column 1 shows the distribution for the Control Group, Column 2 shows the distribution for the Status Quo Group, Column 3 shows the distribution for the Peer Effect Group, Column 4 shows the distribution for the Status Quo and Peer Effect Group ("PE + Status Quo") and Column 5 shows the overall distribution in the sample.

The demographics of our sample are similar to U.S. demographics in many key aspects (Table 4.A.1). For instance, roughly 76% of the U.S. population is white (USCensusBureau, 2021) and in our sample white respondents account for 74% of the participants. Our sample also closely matches the general U.S. population with respect to income distribution, percentage of republicans and education levels (USCensusBureau, 2021). However, there are some differences in the composition of our sample and that of the US population. For example, 58% of our sample is composed by females, whereas the percentage of females in US is about 51% (World Bank, 2019). Our sample is also younger than the general

		(Total)		(Control)		(Status Quo)		(Peer Effect)		(SQ+ PE)	
St. Nr.	Statement	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
1	Covid PASS is important to fight Covid-19	6.54	3.35	6.14	3.33	6.62	3.30	6.59	3.42	6.80	3.32
2	A Covid PASS can help preventing new variants of Covid-19 that might render current Covid-19 vaccines ineffective	6.29	3.40	5.90	3.39	6.22	3.40	6.34	3.41	6.68	3.37
3	A Covid PASS is key to return to normal quickly and safely	6.16	3.38	5.78	3.40	6.19	3.29	6.17	3.44	6.52	3.37
4	A Covid PASS is an extreme limitation to the individual liberties of Americans	3.11	3.45	3.29	3.44	2.91	3.39	3.31	3.58	2.90	3.37
5	A Covid PASS could harm the U.S. social fabric	2.91	3.32	3.11	3.34	2.83	3.29	3.04	3.36	2.64	3.27
6	A Covid PASS poses severe dangers to Americans' data privacy	3.03	3.36	3.21	3.31	2.88	3.35	3.17	3.42	2.86	3.34
7	It is unfair that people with a Covid PASS can travel internationally, while individuals without it cannot	2.72	3.38	2.73	3.39	2.51	3.25	2.95	3.49	2.70	3.38
8	Allowing people with a Covid PASS to travel to countries with lower access to vaccines and potentially come into contact with unvaccinated locals is unfair	3.66	3.21	3.68	3.17	3.55	3.14	3.91	3.27	3.49	3.25
9	A Covid PASS could be easily forged	5.88	2.97	5.95	3.00	5.87	2.93	5.95	2.95	5.74	2.99
10	A Covid PASS would induce more people to get vaccinated	6.17	2.81	6.10	2.76	6.19	2.79	6.11	2.92	6.29	2.75
11	ONLY people with a Covid PASS should be allowed to board INTERNATIONAL flights	6.30	3.52	6.10	3.52	6.31	3.48	6.35	3.55	6.46	3.54
12	If a Covid PASS is implemented, I would intentionally infect myself with Covid-19 to obtain it	0.57	1.64	0.58	1.68	0.59	1.67	0.55	1.58	0.56	1.63
13	Overall, the pros of requiring a Covid PASS for international traveling outweigh the cons	6.65	3.33	6.38	3.36	6.79	3.22	6.52	3.40	6.89	3.32
Obs		3993		999		1000		999		995	

Table 4.2: List of statements with their respective number and summary statistics (mean and standard deviation). Participants were asked their agreement with the following sentences on a scale from 0 to 10.

population, but well represented in all the age groups. Most importantly, the sample is balanced among conditions, allowing for a clear comparison between the control and treatment groups.

4.4.1 Status Quo Treatment

We start by studying the impact of the Status Quo treatment (Table 4.3). We find that respondents included in this group agree more with the three statements capturing the importance of the pass with respect to respondents included in the control group. The difference is sizeable, significant at one percent ($p < 0.001, p = 0.002, p < 0.001$, respectively) and robust to different sets of control variables for all three statements. When turning to unfairness, we find that respondents in the Status Quo agree less with statements 4-7 ($p < 0.001$, $p = 0.014$, $p = 0.004$, $p = 0.008$). Also in this case the difference is sizeable and robust to a battery of controls. Instead, we do not observe a significant difference with respect to statement 8.

Additionally, we do not observe a significant impact of the Status Quo treatment on statements 9 and 12. Therefore, the Status Quo treatment does not induce people to believe that it is easy to forge a Covid pass, nor it induces people to state that they would intentionally get Covid if a pass is introduced. Similarly, the Status Quo does not lead

Nr. Stmt	N	β_{SQ}	p_{SQ}	β_{PE}	p_{PE}	β_{PE+SQ}	p_{PE+SQ}
1	3705	0.525	<0.001	0.56	<0.001	0.707	<0.001
2	3704	0.404	0.002	0.544	<0.001	0.88	<0.001
3	3696	0.471	<0.001	0.48	<0.001	0.792	<0.001
4	3656	-0.413	0.001	-0.101	0.438	-0.485	<0.001
5	3639	-0.308	0.014	-0.195	0.128	-0.527	<0.001
6	3636	-0.364	0.004	-0.188	0.137	-0.443	<0.001
7	3634	-0.331	0.008	0.0755	0.566	-0.134	0.302
8	3664	-0.207	0.137	0.175	0.218	-0.264	0.059
9	3703	-0.09	0.488	-0.0582	0.66	-0.221	0.094
10	3701	0.107	0.362	0.0308	0.797	0.17	0.141
11	3693	0.305	0.024	0.302	0.027	0.361	0.008
12	3579	0.0314	0.681	-0.0094	0.897	0.0046	0.951
13	3690	0.494	<0.001	0.24	0.055	0.592	<0.001

Table 4.3: OLS beta coefficients deriving from regressions with the statements as the dependent variable and a binary variable to measure the impact of being in the treatment groups with respect to the Control group. The regressions are ran controlling for demographics, vaccination status, frequency of travel and trust levels of the participants. Tables of the regressions output are included in the Appendix.

respondents to state that more people will get vaccinated if a pass is introduced (statement 10). Additionally, with respect to the statement 11 we observe that the Status Quo leads respondents to agree more with the idea that only people with a Covid pass should be able to board international flights ($p = 0.024$).

Last, respondents in the Status Quo condition agree more with statement 13 ($p < 0.001$), and therefore consider the pros of a Covid pass to outweigh its cons. Table 4.3 presents the results of regressions ran with the statement as a dependent variable, the treatment as the main independent variable and controls for demographics, vaccination status and trust levels of the participants. We refer the reader to the Appendix for the full regression tables, including the results from regressions with different sets of controls.

To summarise, we conclude that the status quo bias is highly effective in increasing the perceived importance of the Covid pass (statements 1-3), in reducing its perceived unfairness (statements 4-7, with the exception of statement 8), and overall increases the support for the Covid pass (statement 13).

4.4.2 Peer Effects Treatment

As for the Peer Effects treatment, we find that respondents included in this group agree more with the three statements capturing the importance of the pass with respect to respondents included in the control group (see Table 4.3). The magnitude of the effects is large, statistically significant ($p < 0.001$ for all statements) and robust to various sets of control variables for all three statements. When turning to unfairness, instead, we observe that the Peer Effects treatment is not effective. The Peer Effects treatment does not impact the level of agreement with statement 9 and 12, and it does not lead respondents to state that more people will get vaccinated if a pass is introduced (statement 10). Last, respondents in the Peer Effects condition agree more with the idea that the pros of a Covid pass outweigh the cons (statement 13), but the result is weaker than for the Status Quo ($p = 0.55$). Table 4.3 presents the results of regressions ran with the statement as a dependent variable, the treatments as the main independent variable and controls for demographics, vaccination status, frequency of travel and trust levels of the participants. We refer the reader to the Appendix for the full regression tables, including the results from regressions with different sets of controls.

Overall, the peer effects condition has a positive and statistically significant impact on the perceived importance of the Covid pass (statements 1-3), but it has a limited impact on the perceived unfairness (statements 4, 6, 7, 8 with statement 5 being the exception). Moreover, it increases the overall support for the Covid pass (statement 13).

Status Quo + Peer Effects Treatment

Then, we turn to studying the impact of the two nudges when they are used simultaneously. Starting with the statements on the importance of the pass, we find that the joint impact of the nudges is statistically significant ($p < 0.001$ for all statements) and larger than the impact of both nudges used separately (Table 4.3), showing weak additionality in the treatments' effects. For instance, for Statement 2 the joint impact of the two nudges is 218% larger than the effect of the Status Quo alone and 162% larger than that of peer effect.

Combining the two nudges is also very effective in reducing the perceived level of unfairness. Respondents in this condition agree less with statements 4, 5, 6 and 8 ($p < 0.001$, $p < 0.001$, $p < 0.001$, $p = 0.059$ respectively). In line with the Status Quo and the Peer Effects conditions, for statements 9, 10 and 12 we observe no significant differences between this condition and the control. Instead, we see that for statement 11 the joint impact of the two treatments is slightly larger and more statistically significant ($p = 0.008$) than that of the status quo and the peer effects when used separately.

Last, this treatment is the most effective in persuading people that the pros of the Covid pass outweigh the cons (statement 13) ($p < 0.001$).

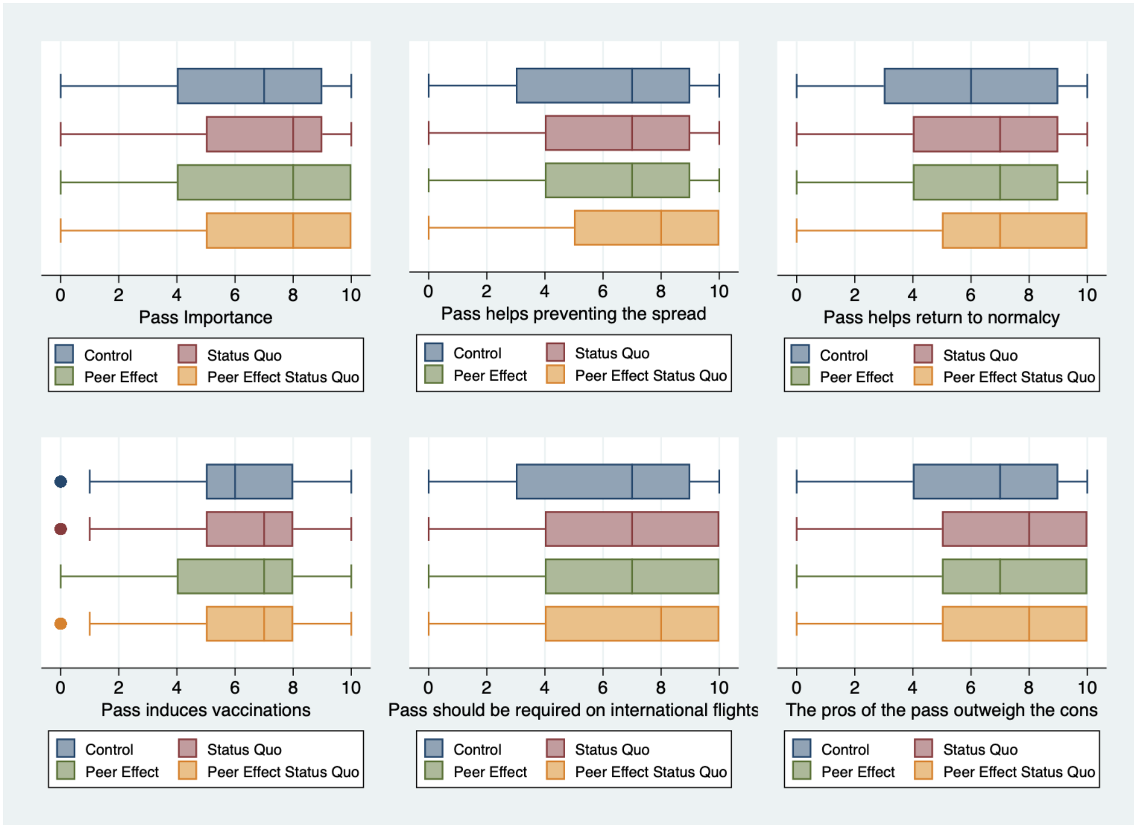

Figure 4.4: Summary of results for the statements meant to capture positive attributes of the Covid pass (statements 1-3, 10, 11 and 13). The boxplots show the distribution of responses in the Control, Status Quo, Peer Effects and Peer Effects and Status Quo groups without any additional control. A higher value corresponds to more favourable attitudes towards the pass.

Table 4.3 presents the results of regressions ran with the statement as a dependent variable, the treatment as the main independent variable and controls for demographics, vaccination status, frequency of travel and trust levels of the participants. We refer the reader to the Appendix for the full regression tables, including the results from regressions with different sets of controls.

Overall, for virtually all statements we find that the two treatments used together have a stronger impact. Figures 4.4 and 4.5 summarises our findings.

To further ensure that our results are robust, we carry out a post hoc test to estimate the marginal effect of the combination of the two nudges relative to the effect of each one separately. The results are included in the Appendix and are consistent with the results reported in Table 4.3.

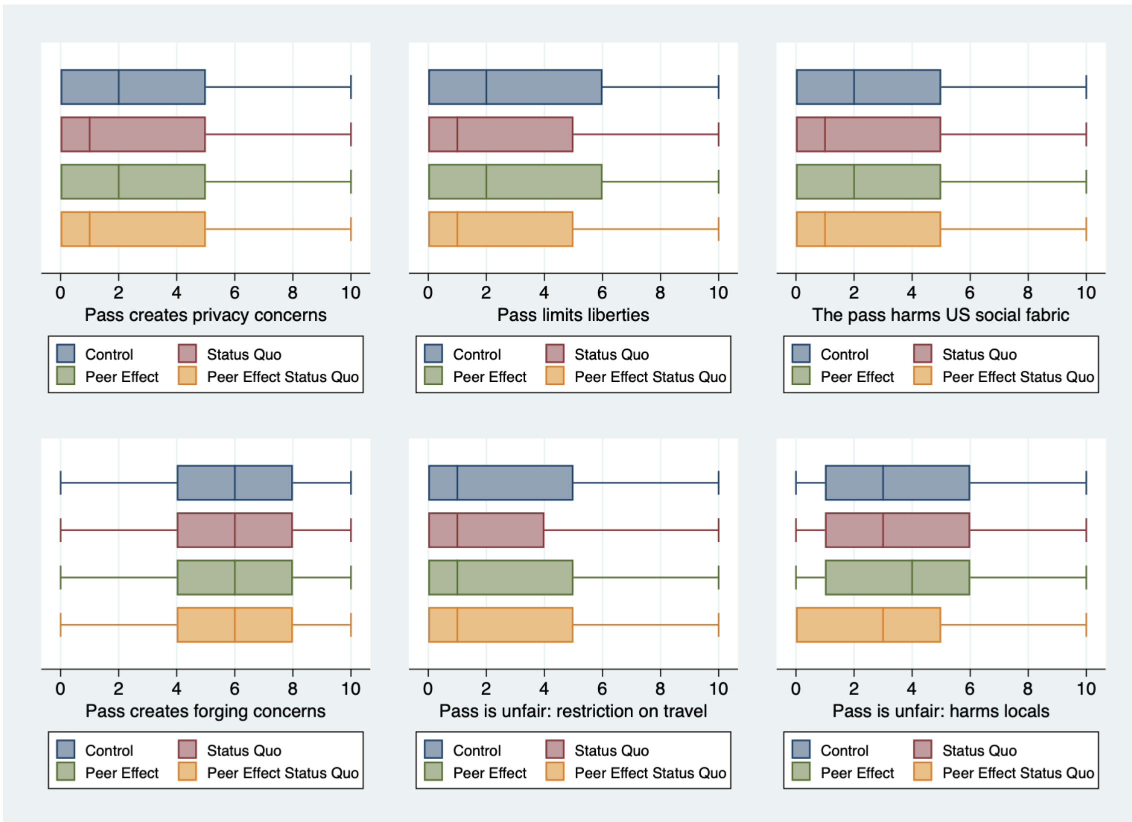

Figure 4.5: Summary of results for the statements meant to capture negative attributes of the Covid pass (statements 4-9). The boxplots show the distribution of responses in the Control, Status Quo, Peer Effects and Peer Effects and Status Quo groups without any additional control. A lower value corresponds to more favourable attitudes towards the pass.

Status	**N**	β_{SQ}	p_{SQ}	β_{PE}	p_{PE}	β_{PE+SQ}	p_{PE+SQ}
Unvaccinnated	1158	0.0124	0.897	-0.12	0.238	-0.01	0.919
One Dose	433	-0.275	0.059	-0.0807	0.501	0.103	0.31
Vaccinated	2121	-0.03	0.494	0.007	0.879	-0.026	0.572
All Sample	3716	-0.0535	0.279	-0.07	0.169	-0.033	0.505

Table 4.4: OLS beta coefficients deriving from regressions with the intention to get vaccinated as the dependent variable and a binary variable to measure the impact of being in the treatment groups with respect to the Control group. The regressions are ran controlling for demographics, vaccination status, frequency of travel and trust levels of the participants. Tables of the regressions output are included in the Appendix.

Intention to get Vaccinated

Last, we turn to investigate whether the treatments affect the intention to get vaccinated if a Covid pass is introduced. The results are reported in Table 4.4. We carry out the analysis considering separately the respondents who have completed a cycle of vaccination, the respondents who have received only one dose, and respondents who have not received a dose yet.

We find that the treatments do not have a negative impact on the intention to get vaccinated in case a Covid pass is introduced for any of these groups. Moreover, we find that the treatments do not have a negative impact also when aggregating the three groups (Table 4.4 and in the Appendix).

Thus, the introduction of a Covid pass is unlikely to negatively affect intentions to get vaccinated.

Discussion

Our experiment revealed that the status quo bias and peer effects can be used together as an effective mean to increase support for the Covid pass, without reducing intention to get vaccinated. These findings have both immediate policy implications and broader theoretical implications.

Policy Implications

Covid passes could play a crucial role in restarting large scale international travelling. However, for them to be successful they must be perceived as both important and fair by the general public. Our results can aid policymakers in ensuring that these conditions are met.

Flying without being vaccinated imposes significant externalities on the country of destination, the other passengers on the flight, and society at large. As noted by Sunstein (2015), nudges aimed at mitigating a negative externality are not particularly controversial from an ethical perspective. The only relevant issue is whether they are effective. From this perspective, we find that both the status quo and peer effects are highly effective in increasing the support for the Covid pass. Most importantly, our results suggest that policymakers who want to increase the support for the Covid pass should rely on the two nudges simultaneously, as this allows them to both increase the perceived importance and the perceived fairness of the Covid pass. In fact, while the relationship between the nudges is not synergistic but weakly additive, the cost of each nudge is likely to be minimal and their combined effect is larger. However, so policymakers often neglected to flag that requiring proof of vaccination for international travelling is not unprecedented, and that in the case of Covid it would be opposed by only a minority of people e.g., Il Messaggero (2021).

Nevertheless, in some contexts policymakers and private companies might not have the possibility to employ both nudges. For instance, according to the Advertising Research Foundation (ARF) 6 seconds TV advertising are very effective in commanding more attention per second than longer advertisements (Marketing Dive, 2018). For such short communications, policymakers and private companies might have to focus on a single nudge. In this case, if they intend to emphasise the importance of the Covid pass they should rely on the peer effects nudge, whereas if they intend to flag the fairness of the pass they should build on the status quo bias.

Theoretical Implications

At a theoretical level, our work contributes to two strands of literature that are gaining momentum: (*i*) the study of interactions among nudges; and (*ii*) behavioural spillovers triggered by nudges.

The literature on interaction among nudges is in its infancy and, to the best of our knowledge, there are no studies testing the interaction between peer effects and the status quo bias, especially in health-related domains. As these nudges are among the most widely studied in the literature and are effective in many domains, it is important to understand whether they can be used together or if their joint use is likely to backfire. Our results reveal that at least in relation to Covid vaccine pass, the status quo and the peer effects nudges are effective together and their effects are weakly additive.

While our results refer to a very unique setting, there are reasons to believe that the status quo bias and the peer effects could often be in a weakly additive relationship. First, by definition, a peer effects nudge as the one used in our experiment can be implemented only for policies that already have a fair amount of support. Therefore, it is likely that for these policies the marginal returns from policy pressure are diminishing at a fairly fast rate. This argument holds both at society level, as greater support implies that there are only a few people left to convince, and at the individual level, where support is already high and cannot further increase by much. This might make it unlikely to observe a synergistic relationship when using the status quo in combination with other nudges.

Second, while they exploit different mechanisms, there is a connection between the two forms of nudges, as they both rely on social influence. Social psychology distinguishes between two main forms of social influence: informational social influence (telling people what is commonly done) and normative social influence (informing them about what is widely approved) (Fiske, 2018; Deutsch and Gerard, 1955). The nudges we implemented in this paper are likely to stimulate both forms of social influence. In fact, the status quo bias suggests that *in the past* there was sufficient support for the policy that it was implemented, whereas the peer effects suggests that *today* there is widespread support for the policy in question. The interaction of informational and normative social influence implicitly pushes the individual in the same direction, making it reasonable to expect some compounding in the effects of the two nudges.

Moreover, as neither on the two interventions relies on monetary incentives, it is unlikely that extrinsic motivations would crowd out the intrinsic motivations triggered by the nudges. For these reasons, we suggest that combining status quo and peer effects is highly unlikely to backfire.

Additionally, we extend the literature on behavioural spillovers by investigating whether nudges on highly topical issues can generate a backlash on other key behaviours. We observe that in this context neither of the treatments had a negative impact on the intention to get vaccinated, thus suggesting that negative spillovers are not going to offset the positive impact of these nudges.

Limitations of the Analysis and Future Research

From a methodological standpoint, our study suffers from two limitations. First, we carry out an online experiment, and hence – like with every online experiment – one can question its external validity. This is partially alleviated by the heterogeneous composition of our sample and its large size. Second, while we rely on a large sample that closely matches the U.S. population along key variables, our sample is not representative. However, online experiments with non-representative samples are widely used across many disciplines and have been proven to be a reliable source of information, with a good degree of generalisability (Mullinix et al., 2015). Moreover, the magnitude of the coefficients is large and robust to different sets of controls, suggesting that our results are likely to be informative even if the sample is not representative.

Additionally, the effect of our treatments is also likely to be context dependent. For instance, it is possible that the impact of peer effects treatment might change, once the percentage of people opposing the Covid pass changes. Therefore, it is of key importance to implement these nudges before too many people start opposing Covid pass. Last, we do not include a manipulation check in our experiment.

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4.A Appendix

4.A.1 Demographics and Summary Statistics

Table 4.A.1: Demographics

	Group														
	Control			**Status Quo**			**Peer Effect**			**PE + Status Quo**			**Total**		
	No.	Col %	Cum %	No.	Col %	Cum %	No.	Col %	Cum %	No.	Col %	Cum %	No.	Col %	Cum %
Political Orientation															
Republican	167	16.7	16.7	165	16.5	16.5	163	16.3	16.3	163	16.4	16.4	658	16.5	16.5
Democrat	571	57.2	73.9	575	57.5	74.0	573	57.4	73.7	550	55.3	71.7	2269	56.8	73.3
Other or No Strong Preference	261	26.1	100.0	260	26.0	100.0	263	26.3	100.0	282	28.3	100.0	1066	26.7	100.0
Total	999	100.0		1000	100.0		999	100.0		995	100.0		3993	100.0	
Gender															
Other/Prefer not to declare	32	3.2	3.2	20	2.0	2.0	30	3.0	3.0	23	2.3	2.3	105	2.6	2.6
Female	551	55.2	58.4	582	58.2	60.2	607	60.8	63.8	553	55.6	57.9	2293	57.4	60.1
Male	416	41.6	100.0	398	39.8	100.0	362	36.2	100.0	419	42.1	100.0	1595	39.9	100.0
Income															
Less than $10,000	56	5.6	5.6	53	5.3	5.3	66	6.6	6.6	62	6.2	6.2	237	5.9	5.9
$10,000 to $19,999	63	6.3	11.9	64	6.4	11.7	62	6.2	12.8	87	8.8	15.0	276	6.9	12.9
$20,000 to $29,999	93	9.3	21.2	85	8.5	20.2	104	10.4	23.3	82	8.3	23.3	364	9.1	22.0
$30,000 to $39,999	81	8.1	29.4	99	9.9	30.1	95	9.5	32.8	96	9.7	32.9	371	9.3	31.3
$40,000 to $49,999	106	10.6	40.0	106	10.6	40.7	82	8.2	41.0	71	7.2	40.1	365	9.2	40.5
$50,000 to $59,999	112	11.2	51.2	111	11.1	51.9	93	9.3	50.4	82	8.3	48.3	398	10.0	50.4
$60,000 to $69,999	74	7.4	58.6	76	7.6	59.5	81	8.1	58.5	82	8.3	56.6	313	7.9	58.3
$70,000 to $79,999	85	8.5	67.1	66	6.6	66.1	75	7.5	66.0	90	9.1	65.7	316	7.9	66.2
$80,000 to $89,999	42	4.2	71.3	55	5.5	71.6	46	4.6	70.6	58	5.8	71.5	201	5.0	71.3
$80,000 to $89,999	54	5.4	76.8	57	5.7	77.3	55	5.5	76.1	53	5.3	76.8	219	5.5	76.7
$90,000 to $99,999	155	15.5	92.3	142	14.2	91.5	139	13.9	90.1	151	15.2	92.0	587	14.7	91.5
$150,000 or more	77	7.7	100.0	85	8.5	100.0	99	9.9	100.0	79	8.0	100.0	340	8.5	100.0
Education															
Less than high school degree	8	0.8	0.8	7	0.7	0.7	14	1.4	1.4	7	0.7	0.7	36	0.9	0.9
High school graduate	103	10.3	11.1	104	10.4	11.1	102	10.2	11.6	109	11.0	11.7	418	10.5	11.4
Some college but no degree	206	20.6	31.7	230	23.0	34.1	230	23.0	34.6	227	22.8	34.5	893	22.4	33.8
Associate degree in college (2-year)	93	9.3	41.0	84	8.4	42.5	109	10.9	45.5	111	11.2	45.7	397	9.9	43.7
Bachelor's degree in college	400	40.0	81.1	373	37.3	79.9	347	34.7	80.3	371	37.3	83.0	1491	37.4	81.1
Master's or Professional Degree	176	17.6	98.7	177	17.7	97.6	169	16.9	97.2	148	14.9	97.9	670	16.8	97.8
Doctoral degree	13	1.3	100.0	24	2.4	100.0	28	2.8	100.0	21	2.1	100.0	86	2.2	100.0
Age															
18-25 years old	253	25.3	25.3	250	25.0	25.0	218	21.8	21.8	240	24.1	24.1	961	24.1	24.1
26-35 years old	343	34.3	59.7	354	35.4	60.4	358	35.8	57.7	317	31.9	56.0	1372	34.4	58.4
36-45 years old	185	18.5	78.2	179	17.9	78.3	189	18.9	76.6	194	19.5	75.5	747	18.7	77.1
46-55 years old	91	9.1	87.3	109	10.9	89.2	101	10.1	86.7	108	10.9	86.3	409	10.2	87.4
56-65 years old	64	6.4	93.7	50	5.0	94.2	61	6.1	92.8	73	7.3	93.7	248	6.2	93.6
66-75 years old	21	2.1	95.8	19	1.9	96.1	24	2.4	95.2	31	3.1	96.8	95	2.4	96.0
>75 years old	42	4.2	100.0	39	3.9	100.0	48	4.8	100.0	32	3.2	100.0	161	4.0	100.0
Full/part time employment	659	66.0	100.0	642	64.2	100.0	649	65.0	100.0	643	64.6	100.0	2593	64.9	100.0
Student	106	10.6	100.0	117	11.7	100.0	127	12.7	100.0	120	12.1	100.0	470	11.8	100.0
White	741	74.2	100.0	761	76.1	100.0	730	73.1	100.0	709	71.3	100.0	2941	73.7	100.0

Table 4.A.2: Summary Statistics

	(Total)		(Control)		(Status Quo)		(Peer Effect)		(SQ+ PE)	
Statement Nr.	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
1	6.54	3.35	6.14	3.33	6.62	3.30	6.59	3.42	6.80	3.32
2	6.29	3.40	5.90	3.39	6.22	3.40	6.34	3.41	6.68	3.37
3	6.16	3.38	5.78	3.40	6.19	3.29	6.17	3.44	6.52	3.37
4	3.11	3.45	3.29	3.44	2.91	3.39	3.31	3.58	2.90	3.37
5	2.91	3.32	3.11	3.34	2.83	3.29	3.04	3.36	2.64	3.27
6	3.03	3.36	3.21	3.31	2.88	3.35	3.17	3.42	2.86	3.34
7	2.72	3.38	2.73	3.39	2.51	3.25	2.95	3.49	2.70	3.38
8	3.66	3.21	3.68	3.17	3.55	3.14	3.91	3.27	3.49	3.25
9	5.88	2.97	5.95	3.00	5.87	2.93	5.95	2.95	5.74	2.99
10	6.17	2.81	6.10	2.76	6.19	2.79	6.11	2.92	6.29	2.75
11	6.30	3.52	6.10	3.52	6.31	3.48	6.35	3.55	6.46	3.54
12	0.57	1.64	0.58	1.68	0.59	1.67	0.55	1.58	0.56	1.63
13	6.65	3.33	6.38	3.36	6.79	3.22	6.52	3.40	6.89	3.32
Obs	3993		999		1000		999		995	

4.A.2 Regression tables for the statements capturing respondents' support for the pass

Table 4.A.3: Determinants of agreement with the importance of a COVID pass to fight the pandemic

	(1) Pass importance	(2) Pass importance	(3) Pass importance	(4) Pass importance	(5) Pass importance	(6) Pass importance
Status Quo	0.478***	0.478***	0.507***	0.507***	0.519***	0.525***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Peer Effect	0.449***	0.449***	0.489***	0.489***	0.564***	0.560***
	(0.003)	(0.003)	(0.001)	(0.001)	(0.000)	(0.000)
Peer Effect Status Quo	0.665***	0.665***	0.713***	0.713***	0.711***	0.707***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age			0.0100**	0.0100**	0.00385	0.00542
			(0.028)	(0.028)	(0.331)	(0.171)
Income			0.0321**	0.0321**	-0.00303	-0.0114
			(0.038)	(0.038)	(0.825)	(0.408)
Female			0.0321	0.0321	0.165*	0.182**
			(0.755)	(0.755)	(0.061)	(0.039)
White			-0.197*	-0.197*	-0.245**	-0.215**
			(0.097)	(0.097)	(0.017)	(0.036)
Political Scale			-0.482***	-0.482***	-0.297***	-0.294***
			(0.000)	(0.000)	(0.000)	(0.000)
Education			0.247***	0.247***	0.128***	0.0972***
			(0.000)	(0.000)	(0.000)	(0.010)
In full or part time employment			-0.00658	-0.00658	-0.110	-0.148
			(0.961)	(0.961)	(0.330)	(0.191)
Student			0.855***	0.855***	0.394**	0.360**
			(0.000)	(0.000)	(0.018)	(0.032)
Republican			-1.080***	-1.080***	-0.490***	-0.516***
			(0.000)	(0.000)	(0.002)	(0.001)
Trust in Federal Government					0.172***	0.170***
					(0.000)	(0.000)
Trust in State Government					-0.0713***	-0.0742***
					(0.003)	(0.002)
Trust in CDC					0.452***	0.455***
					(0.000)	(0.000)
Trust in Pharmaceutical companies					0.0521**	0.0517**
					(0.043)	(0.044)
Trust in Tech companies					0.0662**	0.0616**
					(0.012)	(0.019)
Frequency of travel						0.150***
						(0.000)
Constant	6.139***	6.139***	5.949***	5.949***	2.798***	2.770***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3977	3977	3784	3784	3705	3705
Adjusted R^2	0.005	0.005	0.153	0.153	0.387	0.388

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.A.4: Determinants of agreement with the COVID pass helping to reduce the spread of new variants of the virus

	(1) Pass prevents the spread	(2) Pass prevents the spread	(3) Pass prevents the spread	(4) Pass prevents the spread	(5) Pass prevents the spread	(6) Pass prevents the spread
Status Quo	0.326**	0.326**	0.393***	0.393***	0.399***	0.404***
	(0.032)	(0.032)	(0.007)	(0.007)	(0.003)	(0.002)
Peer Effect	0.444***	0.444***	0.480***	0.480***	0.547***	0.544***
	(0.004)	(0.004)	(0.001)	(0.001)	(0.000)	(0.000)
Peer Effect Status Quo	0.787***	0.787***	0.874***	0.874***	0.882***	0.880***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age			0.00527	0.00527	0.0000639	0.00115
			(0.259)	(0.259)	(0.988)	(0.786)
Income			0.0351**	0.0351**	0.00649	0.000665
			(0.026)	(0.026)	(0.656)	(0.964)
Female			-0.109	-0.109	0.0143	0.0259
			(0.301)	(0.301)	(0.880)	(0.784)
White			-0.0234	-0.0234	-0.0766	-0.0562
			(0.847)	(0.847)	(0.486)	(0.611)
Political Scale			-0.487***	-0.487***	-0.316***	-0.314***
			(0.000)	(0.000)	(0.000)	(0.000)
Education			0.196***	0.196***	0.0863**	0.0652
			(0.000)	(0.000)	(0.025)	(0.100)
In full or part time employment			-0.125	-0.125	-0.243**	-0.269**
			(0.353)	(0.353)	(0.042)	(0.025)
Student			0.663***	0.663***	0.240	0.216
			(0.001)	(0.001)	(0.188)	(0.238)
Republican			-0.968***	-0.968***	-0.454***	-0.472***
			(0.000)	(0.000)	(0.007)	(0.005)
Trust in Federal Government					0.162***	0.162***
					(0.000)	(0.000)
Trust in State Government					-0.0692***	-0.0712***
					(0.008)	(0.007)
Trust in CDC					0.407***	0.409***
					(0.000)	(0.000)
Trust in Pharmaceutical companies					0.0501*	0.0500*
					(0.072)	(0.073)
Trust in Tech companies					0.0413	0.0380
					(0.132)	(0.166)
Frequency of travel						0.104**
						(0.022)
Constant	5.897***	5.897***	6.104***	6.104***	3.306***	3.286***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3974	3974	3781	3781	3704	3704
Adjusted R^2	0.006	0.006	0.141	0.141	0.320	0.321

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.A.5: Determinants of agreement with the COVID pass helping the return to normalcy

	(1) Pass helps return to normalcy	(2) Pass helps return to normalcy	(3) Pass helps return to normalcy	(4) Pass helps return to normalcy	(5) Pass helps return to normalcy	(6) Pass helps return to normalcy
Status Quo	0.409***	0.409***	0.470***	0.470***	0.462***	0.471***
	(0.006)	(0.006)	(0.001)	(0.001)	(0.000)	(0.000)
Peer Effect	0.395**	0.395**	0.447***	0.447***	0.487***	0.480***
	(0.010)	(0.010)	(0.003)	(0.003)	(0.000)	(0.000)
Peer Effect Status Quo	0.737***	0.737***	0.812***	0.812***	0.799***	0.792***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age			0.00541	0.00541	-0.00129	0.00111
			(0.247)	(0.247)	(0.751)	(0.785)
Income			0.0383**	0.0383**	0.00239	-0.0105
			(0.015)	(0.015)	(0.864)	(0.457)
Female			-0.000601	-0.000601	0.139	0.164*
			(0.995)	(0.995)	(0.127)	(0.071)
White			-0.149	-0.149	-0.155	-0.110
			(0.215)	(0.215)	(0.140)	(0.293)
Political Scale			-0.475***	-0.475***	-0.302***	-0.297***
			(0.000)	(0.000)	(0.000)	(0.000)
Education			0.198***	0.198***	0.0885**	0.0416
			(0.000)	(0.000)	(0.017)	(0.275)
In full or part time employment			0.0149	0.0149	-0.100	-0.160
			(0.913)	(0.913)	(0.393)	(0.173)
Student			0.687***	0.687***	0.251	0.195
			(0.000)	(0.000)	(0.155)	(0.269)
Republican			-0.960***	-0.960***	-0.437***	-0.478***
			(0.000)	(0.000)	(0.006)	(0.002)
Trust in Federal Government					0.152***	0.150***
					(0.000)	(0.000)
Trust in State Government					-0.0726***	-0.0771***
					(0.004)	(0.002)
Trust in CDC					0.428***	0.432***
					(0.000)	(0.000)
Trust in Pharmaceutical companies					0.109***	0.108***
					(0.000)	(0.000)
Trust in Tech companies					0.0672**	0.0603**
					(0.013)	(0.026)
Frequency of travel						0.231***
						(0.000)
Constant	5.779***	5.779***	5.857***	5.857***	2.747***	2.707***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3965	3965	3772	3772	3696	3696
Adjusted R^2	0.005	0.005	0.137	0.137	0.367	0.372

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.A.6: Determinants of agreement with the COVID pass being a limitation of liberties

	(1) Pass limits liberties	(2) Pass limits liberties	(3) Pass limits liberties	(4) Pass limits liberties	(5) Pass limits liberties	(6) Pass limits liberties
Status Quo	-0.372**	-0.372**	-0.388***	-0.388***	-0.409***	-0.413***
	(0.016)	(0.016)	(0.005)	(0.005)	(0.001)	(0.001)
Peer Effect	0.0294	0.0294	-0.0141	-0.0141	-0.103	-0.101
	(0.853)	(0.853)	(0.922)	(0.922)	(0.433)	(0.438)
Peer Effect Status Quo	-0.383**	-0.383**	-0.452***	-0.452***	-0.486***	-0.485***
	(0.013)	(0.013)	(0.001)	(0.001)	(0.000)	(0.000)
Age			0.00395	0.00395	0.00844**	0.00771*
			(0.388)	(0.388)	(0.039)	(0.059)
Income			-0.0249*	-0.0249*	0.000415	0.00421
			(0.097)	(0.097)	(0.976)	(0.767)
Female			0.0332	0.0332	-0.0814	-0.0891
			(0.742)	(0.742)	(0.369)	(0.326)
White			0.102	0.102	0.160	0.147
			(0.385)	(0.385)	(0.134)	(0.173)
Political Scale			0.647***	0.647***	0.460***	0.459***
			(0.000)	(0.000)	(0.000)	(0.000)
Education			-0.276***	-0.276***	-0.175***	-0.161***
			(0.000)	(0.000)	(0.000)	(0.000)
In full or part time employment			0.175	0.175	0.257**	0.275**
			(0.188)	(0.188)	(0.029)	(0.020)
Student			-0.816***	-0.816***	-0.396**	-0.379**
			(0.000)	(0.000)	(0.017)	(0.022)
Republican			1.040***	1.040***	0.587***	0.599***
			(0.000)	(0.000)	(0.001)	(0.001)
Trust in Federal Government					-0.0827***	-0.0822***
					(0.006)	(0.006)
Trust in State Government					0.0692***	0.0703***
					(0.005)	(0.005)
Trust in CDC					-0.462***	-0.464***
					(0.000)	(0.000)
Trust in Pharmaceutical companies					-0.0686**	-0.0683**
					(0.011)	(0.011)
Trust in Tech companies					0.0296	0.0318
					(0.284)	(0.251)
Frequency of travel						-0.0689
						(0.121)
Constant	3.286***	3.286***	2.546***	2.546***	5.245***	5.259***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3908	3908	3727	3727	3656	3656
Adjusted R^2	0.002	0.002	0.225	0.225	0.383	0.383

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.A.7: Determinants of agreement with the COVID pass harming the US social fabric

	(1) The pass harms US social fabric	(2) The pass harms US social fabric	(3) The pass harms US social fabric	(4) The pass harms US social fabric	(5) The pass harms US social fabric	(6) The pass harms US social fabric
Status Quo	-0.280*	-0.280*	-0.293**	-0.293**	-0.305**	-0.308**
	(0.063)	(0.063)	(0.036)	(0.036)	(0.015)	(0.014)
Peer Effect	-0.0689	-0.0689	-0.104	-0.104	-0.195	-0.195
	(0.650)	(0.650)	(0.460)	(0.460)	(0.127)	(0.128)
Peer Effect Status Quo	-0.468***	-0.468***	-0.498***	-0.498***	-0.528***	-0.527***
	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Age			-0.00272	-0.00272	0.00162	0.00109
			(0.553)	(0.553)	(0.694)	(0.792)
Income			-0.0132	-0.0132	0.0132	0.0160
			(0.372)	(0.372)	(0.334)	(0.251)
Female			-0.0776	-0.0776	-0.184**	-0.190**
			(0.438)	(0.438)	(0.040)	(0.035)
White			0.257**	0.257**	0.310***	0.300***
			(0.024)	(0.024)	(0.003)	(0.004)
Political Scale			0.566***	0.566***	0.393***	0.392***
			(0.000)	(0.000)	(0.000)	(0.000)
Education			-0.217***	-0.217***	-0.121***	-0.111***
			(0.000)	(0.000)	(0.001)	(0.004)
In full or part time employment			0.129	0.129	0.201*	0.214*
			(0.325)	(0.325)	(0.086)	(0.070)
Student			-0.824***	-0.824***	-0.425**	-0.413**
			(0.000)	(0.000)	(0.011)	(0.014)
Republican			0.975***	0.975***	0.514***	0.523***
			(0.000)	(0.000)	(0.002)	(0.002)
Trust in Federal Government					-0.0899***	-0.0894***
					(0.003)	(0.003)
Trust in State Government					0.0803***	0.0811***
					(0.001)	(0.001)
Trust in CDC					-0.431***	-0.432***
					(0.000)	(0.000)
Trust in Pharmaceutical companies					-0.0827***	-0.0825***
					(0.002)	(0.002)
Trust in Tech companies					0.0280	0.0295
					(0.319)	(0.294)
Frequency of travel						-0.0497
						(0.272)
Constant	3.112***	3.112***	2.462***	2.462***	4.998***	5.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3878	3878	3707	3707	3639	3639
Adjusted R^2	0.002	0.002	0.190	0.190	0.346	0.346

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.A.8: Determinants of agreement with the COVID pass creating privacy concerns

	(1) Pass creates privacy concerns	(2) Pass creates privacy concerns	(3) Pass creates privacy concerns	(4) Pass creates privacy concerns	(5) Pass creates privacy concerns	(6) Pass creates privacy concerns
Status Quo	-0.324**	-0.324**	-0.357**	-0.357**	-0.363***	-0.364***
	(0.032)	(0.032)	(0.011)	(0.011)	(0.004)	(0.004)
Peer Effect	-0.0403	-0.0403	-0.0919	-0.0919	-0.188	-0.188
	(0.791)	(0.791)	(0.515)	(0.515)	(0.136)	(0.137)
Peer Effect Status Quo	-0.348**	-0.348**	-0.422***	-0.422***	-0.443***	-0.443***
	(0.021)	(0.021)	(0.003)	(0.003)	(0.000)	(0.000)
Age			0.00596	0.00596	0.0113***	0.0110***
			(0.195)	(0.195)	(0.007)	(0.008)
Income			-0.0291*	-0.0291*	-0.00143	0.0000602
			(0.051)	(0.051)	(0.918)	(0.997)
Female			-0.133	-0.133	-0.260***	-0.263***
			(0.190)	(0.190)	(0.004)	(0.004)
White			0.182	0.182	0.234**	0.228**
			(0.113)	(0.113)	(0.024)	(0.028)
Political Scale			0.591***	0.591***	0.416***	0.415***
			(0.000)	(0.000)	(0.000)	(0.000)
Education			-0.197***	-0.197***	-0.0944**	-0.0890**
			(0.000)	(0.000)	(0.012)	(0.021)
In full or part time employment			0.191	0.191	0.268**	0.275**
			(0.139)	(0.139)	(0.020)	(0.018)
Student			-0.549***	-0.549***	-0.149	-0.143
			(0.002)	(0.002)	(0.379)	(0.401)
Republican			0.933***	0.933***	0.475***	0.480***
			(0.000)	(0.000)	(0.006)	(0.005)
Trust in Federal Government					-0.0838***	-0.0836***
					(0.006)	(0.007)
Trust in State Government					0.0677***	0.0682***
					(0.007)	(0.007)
Trust in CDC					-0.431***	-0.432***
					(0.000)	(0.000)
Trust in Pharmaceutical companies					-0.0925***	-0.0924***
					(0.001)	(0.001)
Trust in Tech companies					0.00284	0.00372
					(0.920)	(0.895)
Frequency of travel						-0.0270
						(0.544)
Constant	3.208***	3.208***	2.249***	2.249***	4.885***	4.891***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3882	3882	3707	3707	3636	3636
Adjusted R^2	0.001	0.001	0.195	0.195	0.361	0.360

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.A.9: Determinants of agreement with the COVID pass being unfair as it allows only people with a COVID pass to travel

	(1) Pass is unfair: travel restriction	(2) Pass is unfair: travel restriction	(3) Pass is unfair: travel restriction	(4) Pass is unfair: travel restriction	(5) Pass is unfair: travel restriction	(6) Pass is unfair: travel restriction
Status Quo	-0.223	-0.223	-0.310**	-0.310**	-0.333***	-0.331***
	(0.138)	(0.138)	(0.025)	(0.025)	(0.008)	(0.008)
Peer Effect	0.215	0.215	0.156	0.156	0.0761	0.0755
	(0.168)	(0.168)	(0.276)	(0.276)	(0.563)	(0.566)
Peer Effect Status Quo	-0.0301	-0.0301	-0.105	-0.105	-0.133	-0.134
	(0.845)	(0.845)	(0.461)	(0.461)	(0.305)	(0.302)
Age			-0.00664	-0.00664	-0.00344	-0.00287
			(0.137)	(0.137)	(0.399)	(0.484)
Income			-0.0440***	-0.0440***	-0.0238*	-0.0267*
			(0.003)	(0.003)	(0.093)	(0.061)
Female			0.0600	0.0600	-0.0275	-0.0215
			(0.552)	(0.552)	(0.765)	(0.816)
White			-0.117	-0.117	-0.0115	-0.00125
			(0.322)	(0.322)	(0.916)	(0.991)
Political Scale			0.619***	0.619***	0.439***	0.440***
			(0.000)	(0.000)	(0.000)	(0.000)
Education			-0.149***	-0.149***	-0.0551	-0.0659*
			(0.000)	(0.000)	(0.149)	(0.091)
In full or part time employment			0.108	0.108	0.158	0.144
			(0.408)	(0.408)	(0.182)	(0.229)
Student			-0.735***	-0.735***	-0.372**	-0.385**
			(0.000)	(0.000)	(0.029)	(0.024)
Republican			0.997***	0.997***	0.545***	0.536***
			(0.000)	(0.000)	(0.002)	(0.003)
Trust in Federal Government					-0.0575*	-0.0580*
					(0.056)	(0.054)
Trust in State Government					0.0672***	0.0663***
					(0.007)	(0.008)
Trust in CDC					-0.447***	-0.446***
					(0.000)	(0.000)
Trust in Pharmaceutical companies					-0.0405	-0.0408
					(0.135)	(0.132)
Trust in Tech companies					0.0379	0.0362
					(0.177)	(0.196)
Frequency of travel						0.0538
						(0.233)
Constant	2.734***	2.734***	2.196***	2.196***	4.629***	4.618***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3872	3872	3697	3697	3634	3634
Adjusted R^2	0.001	0.001	0.199	0.199	0.333	0.333

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.A.10: Determinants of agreement with the COVID pass being unfair as it poses threats to locals when people with the COVID pass travel

	(1)	(2)	(3)	(4)	(5)	(6)
	Pass is unfair: harms locals	Pass is unfair: harms locals	Pass is unfair: harms locals	Pass is unfair: harms locals	Pass is unfair: harms locals	Pass is unfair: harms locals
Status Quo	-0.137	-0.137	-0.191	-0.191	-0.209	-0.207
	(0.336)	(0.336)	(0.181)	(0.181)	(0.132)	(0.137)
Peer Effect	0.225	0.225	0.190	0.190	0.176	0.175
	(0.121)	(0.121)	(0.189)	(0.189)	(0.215)	(0.218)
Peer Effect Status Quo	-0.192	-0.192	-0.247*	-0.247*	-0.263*	-0.264*
	(0.185)	(0.185)	(0.086)	(0.086)	(0.060)	(0.059)
Age			-0.0191***	-0.0191***	-0.0186***	-0.0180***
			(0.000)	(0.000)	(0.000)	(0.000)
Income			-0.0270*	-0.0270*	-0.0165	-0.0195
			(0.090)	(0.090)	(0.298)	(0.220)
Female			0.121	0.121	0.0635	0.0696
			(0.242)	(0.242)	(0.529)	(0.492)
White			-0.284**	-0.284**	-0.215*	-0.205*
			(0.019)	(0.019)	(0.072)	(0.087)
Political Scale			0.264***	0.264***	0.173***	0.174***
			(0.000)	(0.000)	(0.000)	(0.000)
Education			-0.0504	-0.0504	-0.00632	-0.0176
			(0.242)	(0.242)	(0.883)	(0.693)
In full or part time employment			-0.118	-0.118	-0.0896	-0.104
			(0.386)	(0.386)	(0.502)	(0.439)
Student			-0.580***	-0.580***	-0.353*	-0.366*
			(0.004)	(0.004)	(0.079)	(0.070)
Republican			0.788***	0.788***	0.498***	0.488***
			(0.000)	(0.000)	(0.006)	(0.007)
Trust in Federal Government					0.0133	0.0127
					(0.708)	(0.719)
Trust in State Government					0.0427	0.0417
					(0.152)	(0.162)
Trust in CDC					-0.283***	-0.282***
					(0.000)	(0.000)
Trust in Pharmaceutical companies					-0.0734**	-0.0735**
					(0.013)	(0.013)
Trust in Tech companies					0.0402	0.0384
					(0.186)	(0.206)
Frequency of travel						0.0552
						(0.261)
Constant	3.684***	3.684***	4.233***	4.233***	5.749***	5.739***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3912	3912	3732	3732	3664	3664
Adjusted R^2	0.002	0.002	0.053	0.053	0.108	0.108

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.A.11: Determinants of agreement with forging a COVID pass being easy

	(1) Forging concerns	(2) Forging concerns	(3) Forging concerns	(4) Forging concerns	(5) Forging concerns	(6) Forging concerns
Status Quo	-0.0786	-0.0786	-0.0837	-0.0837	-0.0830	-0.0900
	(0.554)	(0.554)	(0.526)	(0.526)	(0.523)	(0.488)
Peer Effect	0.00288	0.00288	-0.0669	-0.0669	-0.0613	-0.0582
	(0.983)	(0.983)	(0.619)	(0.619)	(0.643)	(0.660)
Peer Effect Status Quo	-0.214	-0.214	-0.247*	-0.247*	-0.225*	-0.221*
	(0.112)	(0.112)	(0.066)	(0.066)	(0.089)	(0.094)
Age			0.0190***	0.0190***	0.0244***	0.0227***
			(0.000)	(0.000)	(0.000)	(0.000)
Income			0.0166	0.0166	0.0314**	0.0400***
			(0.258)	(0.258)	(0.033)	(0.007)
Female			0.477***	0.477***	0.415***	0.397***
			(0.000)	(0.000)	(0.000)	(0.000)
White			-0.127	-0.127	-0.172	-0.202*
			(0.261)	(0.261)	(0.124)	(0.071)
Political Scale			0.252***	0.252***	0.223***	0.220***
			(0.000)	(0.000)	(0.000)	(0.000)
Education			-0.143***	-0.143***	-0.0981**	-0.0670*
			(0.000)	(0.000)	(0.011)	(0.092)
In full or part time employment			-0.141	-0.141	-0.0949	-0.0565
			(0.249)	(0.249)	(0.435)	(0.644)
Student			-0.0336	-0.0336	0.147	0.183
			(0.854)	(0.854)	(0.422)	(0.321)
Republican			0.0119	0.0119	-0.0407	-0.0145
			(0.940)	(0.940)	(0.793)	(0.925)
Trust in Federal Government					-0.0829**	-0.0816**
					(0.014)	(0.016)
Trust in State Government					-0.0259	-0.0230
					(0.355)	(0.411)
Trust in CDC					-0.0408	-0.0437*
					(0.102)	(0.079)
Trust in Pharmaceutical companies					-0.116***	-0.116***
					(0.000)	(0.000)
Trust in Tech companies					0.0101	0.0150
					(0.716)	(0.591)
Frequency of travel						-0.153***
						(0.001)
Constant	5.952***	5.952***	5.082***	5.082***	5.755***	5.784***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3972	3972	3784	3784	3703	3703
Adjusted R^2	0.000	0.000	0.046	0.046	0.084	0.086

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.A.12: Determinants of agreement with the COVID inducing more vaccinations

	(1) Pass induces vaccinations	(2) Pass induces vaccinations	(3) Pass induces vaccinations	(4) Pass induces vaccinations	(5) Pass induces vaccinations	(6) Pass induces vaccinations
Status Quo	0.0906	0.0906	0.106	0.106	0.103	0.107
	(0.467)	(0.467)	(0.398)	(0.398)	(0.384)	(0.362)
Peer Effect	0.0172	0.0172	0.0205	0.0205	0.0332	0.0308
	(0.893)	(0.893)	(0.873)	(0.873)	(0.782)	(0.797)
Peer Effect Status Quo	0.194	0.194	0.222*	0.222*	0.174	0.170
	(0.118)	(0.118)	(0.073)	(0.073)	(0.135)	(0.141)
Age			-0.0101**	-0.0101**	-0.0144***	-0.0131***
			(0.012)	(0.012)	(0.000)	(0.000)
Income			0.00840	0.00840	-0.0156	-0.0224*
			(0.541)	(0.541)	(0.232)	(0.087)
Female			-0.199**	-0.199**	-0.105	-0.0913
			(0.029)	(0.029)	(0.216)	(0.284)
White			-0.326***	-0.326***	-0.336***	-0.312***
			(0.002)	(0.002)	(0.001)	(0.002)
Political Scale			-0.189***	-0.189***	-0.0875***	-0.0849***
			(0.000)	(0.000)	(0.001)	(0.002)
Education			0.0826**	0.0826**	0.00511	-0.0194
			(0.027)	(0.027)	(0.885)	(0.593)
In full or part time employment			0.112	0.112	0.00918	-0.0213
			(0.345)	(0.345)	(0.934)	(0.849)
Student			0.559***	0.559***	0.240	0.211
			(0.001)	(0.001)	(0.152)	(0.208)
Republican			-0.355**	-0.355**	0.00467	-0.0169
			(0.030)	(0.030)	(0.974)	(0.907)
Trust in Federal Government					0.0735**	0.0726**
					(0.018)	(0.019)
Trust in State Government					0.00468	0.00235
					(0.858)	(0.928)
Trust in CDC					0.253***	0.255***
					(0.000)	(0.000)
Trust in Pharmaceutical companies					0.0397	0.0395
					(0.133)	(0.136)
Trust in Tech companies					0.0840***	0.0802***
					(0.002)	(0.003)
Frequency of travel						0.121***
						(0.003)
Constant	6.098***	6.098***	6.801***	6.801***	4.858***	4.837***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3967	3967	3779	3779	3701	3701
Adjusted R^2	-0.000	-0.000	0.044	0.044	0.177	0.179

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.A.13: Determinants of agreement with requiring a COVID pass for international flights

	(1) Pass required on international flights	(2) Pass required on international flights	(3) Pass required on international flights	(4) Pass required on international flights	(5) Pass required on international flights	(6) Pass required on international flights
Status Quo	0.206	0.206	0.281*	0.281*	0.302**	0.305**
	(0.190)	(0.190)	(0.062)	(0.062)	(0.025)	(0.024)
Peer Effect	0.251	0.251	0.249	0.249	0.303**	0.302**
	(0.115)	(0.115)	(0.105)	(0.105)	(0.027)	(0.027)
Peer Effect Status Quo	0.357**	0.357**	0.386**	0.386**	0.363***	0.361***
	(0.025)	(0.025)	(0.011)	(0.011)	(0.008)	(0.008)
Age			0.0144***	0.0144***	0.0105**	0.0112***
			(0.003)	(0.003)	(0.014)	(0.009)
Income			0.0301*	0.0301*	-0.00224	-0.00585
			(0.072)	(0.072)	(0.883)	(0.703)
Female			-0.0625	-0.0625	0.0570	0.0644
			(0.566)	(0.566)	(0.557)	(0.507)
White			-0.185	-0.185	-0.212*	-0.200*
			(0.145)	(0.145)	(0.063)	(0.082)
Political Scale			-0.561***	-0.561***	-0.376***	-0.374***
			(0.000)	(0.000)	(0.000)	(0.000)
Education			0.127***	0.127***	0.0214	0.00835
			(0.004)	(0.004)	(0.595)	(0.840)
In full or part time employment			-0.0419	-0.0419	-0.124	-0.140
			(0.769)	(0.769)	(0.323)	(0.268)
Student			0.471**	0.471**	0.0659	0.0507
			(0.022)	(0.022)	(0.729)	(0.791)
Republican			-0.758***	-0.758***	-0.249	-0.260
			(0.000)	(0.000)	(0.137)	(0.120)
Trust in Federal Government					0.127***	0.126***
					(0.000)	(0.000)
Trust in State Government					-0.0678**	-0.0691**
					(0.012)	(0.011)
Trust in CDC					0.467***	0.469***
					(0.000)	(0.000)
Trust in Pharmaceutical companies					0.0796***	0.0794***
					(0.006)	(0.006)
Trust in Tech companies					0.00634	0.00427
					(0.833)	(0.887)
Frequency of travel						0.0642
						(0.179)
Constant	6.101***	6.101***	6.556***	6.556***	3.451***	3.439***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3951	3951	3763	3763	3693	3693
Adjusted R^2	0.001	0.001	0.134	0.134	0.325	0.326

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.A.14: Determinants of agreement with intentionally getting infected with COVID to obtain the COVID pass

	(1) Pass induces intentional infections	(2) Pass induces intentional infections	(3) Pass induces intentional infections	(4) Pass induces intentional infections	(5) Pass induces intentional infections	(6) Pass induces intentional infections
Status Quo	0.0169	0.0169	0.0341	0.0341	0.0234	0.0314
	(0.826)	(0.826)	(0.656)	(0.656)	(0.760)	(0.681)
Peer Effect	-0.0284	-0.0284	-0.00272	-0.00272	-0.00731	-0.00942
	(0.705)	(0.705)	(0.971)	(0.971)	(0.921)	(0.897)
Peer Effect Status Quo	-0.0197	-0.0197	0.0167	0.0167	0.00688	0.00459
	(0.796)	(0.796)	(0.826)	(0.826)	(0.928)	(0.951)
Age			-0.0109***	-0.0109***	-0.0120***	-0.0102***
			(0.000)	(0.000)	(0.000)	(0.000)
Income			-0.0145*	-0.0145*	-0.0191**	-0.0281***
			(0.077)	(0.077)	(0.022)	(0.001)
Female			-0.118**	-0.118**	-0.114**	-0.0957*
			(0.031)	(0.031)	(0.036)	(0.077)
White			-0.0790	-0.0790	-0.0539	-0.0229
			(0.225)	(0.225)	(0.416)	(0.730)
Political Scale			0.0887***	0.0887***	0.0732***	0.0758***
			(0.000)	(0.000)	(0.000)	(0.000)
Education			0.0645***	0.0645***	0.0546**	0.0220
			(0.005)	(0.005)	(0.018)	(0.349)
In full or part time employment			0.236***	0.236***	0.233***	0.191***
			(0.000)	(0.000)	(0.000)	(0.001)
Student			0.0576	0.0576	0.0708	0.0332
			(0.514)	(0.514)	(0.432)	(0.714)
Republican			0.0366	0.0366	0.0392	0.0133
			(0.740)	(0.740)	(0.725)	(0.904)
Trust in Federal Government					0.0305	0.0294
					(0.116)	(0.129)
Trust in State Government					0.00308	0.0000730
					(0.810)	(0.995)
Trust in CDC					-0.0483***	-0.0455***
					(0.001)	(0.001)
Trust in Pharmaceutical companies					0.0271*	0.0266*
					(0.087)	(0.090)
Trust in Tech companies					0.0461***	0.0410***
					(0.002)	(0.005)
Frequency of travel						0.161***
						(0.000)
Constant	0.577***	0.577***	0.466***	0.466***	0.477***	0.445***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	(0.003)
Observations	3784	3784	3624	3624	3579	3579
Adjusted R^2	-0.001	-0.001	0.025	0.025	0.037	0.047

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.A.15: Determinants of agreement with the COVID pass having greater pros than cons

	(1) Pros outweigh cons	(2) Pros outweigh cons	(3) Pros outweigh cons	(4) Pros outweigh cons	(5) Pros outweigh cons	(6) Pros outweigh cons
Status Quo	0.412***	0.412***	0.459***	0.459***	0.491***	0.494***
	(0.005)	(0.005)	(0.001)	(0.001)	(0.000)	(0.000)
Peer Effect	0.146	0.146	0.154	0.154	0.242*	0.240*
	(0.336)	(0.336)	(0.285)	(0.285)	(0.054)	(0.055)
Peer Effect Status Quo	0.514***	0.514***	0.587***	0.587***	0.593***	0.592***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Age			0.0155***	0.0155***	0.0120***	0.0127***
			(0.001)	(0.001)	(0.002)	(0.001)
Income			0.0520***	0.0520***	0.0242*	0.0205
			(0.001)	(0.001)	(0.077)	(0.135)
Female			-0.138	-0.138	-0.0407	-0.0332
			(0.170)	(0.170)	(0.644)	(0.707)
White			0.0761	0.0761	-0.0180	-0.00516
			(0.515)	(0.515)	(0.863)	(0.961)
Political Scale			-0.551***	-0.551***	-0.362***	-0.360***
			(0.000)	(0.000)	(0.000)	(0.000)
Education			0.201***	0.201***	0.0985***	0.0850**
			(0.000)	(0.000)	(0.007)	(0.024)
In full or part time employment			-0.129	-0.129	-0.211*	-0.228**
			(0.328)	(0.328)	(0.061)	(0.045)
Student			0.605***	0.605***	0.197	0.182
			(0.001)	(0.001)	(0.238)	(0.279)
Republican			-1.076***	-1.076***	-0.540***	-0.551***
			(0.000)	(0.000)	(0.001)	(0.000)
Trust in Federal Government					0.0899***	0.0894***
					(0.003)	(0.003)
Trust in State Government					-0.0315	-0.0327
					(0.210)	(0.192)
Trust in CDC					0.490***	0.491***
					(0.000)	(0.000)
Trust in Pharmaceutical companies					0.0382	0.0381
					(0.155)	(0.156)
Trust in Tech companies					0.0106	0.00843
					(0.689)	(0.751)
Frequency of travel						0.0659
						(0.125)
Constant	6.378***	6.378***	6.252***	6.252***	3.103***	3.091***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3942	3942	3756	3756	3690	3690
Adjusted R^2	0.003	0.003	0.174	0.174	0.381	0.381

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.A.3 Factor analysis

```
Factor analysis/correlation                        Number of obs    =      3,639
    Method: principal factors                      Retained factors =          5
    Rotation: (unrotated)                          Number of params =         55
```

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	7.18628	6.41494	0.9111	0.9111
Factor2	0.77134	0.56656	0.0978	1.0089
Factor3	0.20478	0.02751	0.0260	1.0349
Factor4	0.17727	0.07865	0.0225	1.0574
Factor5	0.09862	0.11482	0.0125	1.0699
Factor6	-0.01621	0.02471	-0.0021	1.0678
Factor7	-0.04092	0.01193	-0.0052	1.0626
Factor8	-0.05285	0.00414	-0.0067	1.0559
Factor9	-0.05699	0.00850	-0.0072	1.0487
Factor10	-0.06549	0.00325	-0.0083	1.0404
Factor11	-0.06875	0.03420	-0.0087	1.0317
Factor12	-0.10295	0.04400	-0.0131	1.0186
Factor13	-0.14695	.	-0.0186	1.0000

LR test: independent vs. saturated: chi2(78) = 4.0e+04 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Factor4	Factor5	Uniqueness
pass_impor~e	0.8847	0.2785	0.0718	-0.0427	-0.1010	0.1227
pass_preve~d	0.8057	0.3012	0.0467	-0.0603	-0.1310	0.2372
pass_norma~y	0.8668	0.2857	0.0181	-0.0448	-0.0586	0.1613
pass_limit~y	-0.8783	0.2984	-0.1140	0.0523	-0.0269	0.1230
pass_socia~c	-0.8507	0.2912	-0.1094	0.1176	-0.0344	0.1644
pass_privacy	-0.8421	0.2603	-0.0801	0.1173	-0.0774	0.1970
pass_unfai~l	-0.8231	0.2474	0.0671	-0.1790	0.0762	0.2189
pass_unfai~s	-0.5092	0.2511	0.2729	-0.0142	0.0779	0.5969
pass_forge	-0.3603	0.0362	0.2641	0.1664	0.0005	0.7715
pass_induc~e	0.5484	0.2622	-0.1169	-0.0629	0.1427	0.5925
pass_fligh~r	0.8280	0.1359	-0.0182	0.1952	0.0927	0.2489
pass_inten~n	-0.0973	0.2293	-0.0527	-0.1087	0.0970	0.9139
pass_prosc~s	0.8582	0.1199	-0.0165	0.1603	0.0984	0.2135

Table 4.A.16: Factor analysis results using the first factor to consider all the statements about the pass

	(1) Scores for factor 1	(2) Scores for factor 1	(3) Scores for factor 1	(4) Scores for factor 1	(5) Scores for factor 1	(6) Scores for factor 1
Status Quo	0.119***	0.119***	0.137***	0.137***	0.141***	0.143***
	(0.008)	(0.008)	(0.001)	(0.001)	(0.000)	(0.000)
Peer Effect	0.0535	0.0535	0.0622	0.0622	0.100***	0.1000***
	(0.246)	(0.246)	(0.141)	(0.141)	(0.004)	(0.004)
Peer Effect Status Quo	0.141***	0.141***	0.160***	0.160***	0.180***	0.180***
	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Age			0.00175	0.00175	0.0000631	0.000360
			(0.197)	(0.197)	(0.956)	(0.751)
Income			0.00885**	0.00885**	0.000206	-0.00134
			(0.045)	(0.045)	(0.957)	(0.729)
Female			-0.0115	-0.0115	0.0268	0.0300
			(0.702)	(0.702)	(0.285)	(0.233)
White			-0.0256	-0.0256	-0.0448	-0.0395
			(0.455)	(0.455)	(0.118)	(0.170)
Political Scale			-0.184***	-0.184***	-0.125***	-0.124***
			(0.000)	(0.000)	(0.000)	(0.000)
Education			0.0681***	0.0681***	0.0353***	0.0297***
			(0.000)	(0.000)	(0.001)	(0.005)
In full or part time employment			-0.0165	-0.0165	-0.0483	-0.0559*
			(0.677)	(0.677)	(0.137)	(0.088)
Student			0.236***	0.236***	0.100**	0.0932**
			(0.000)	(0.000)	(0.032)	(0.047)
Republican			-0.317***	-0.317***	-0.161***	-0.165***
			(0.000)	(0.000)	(0.001)	(0.000)
Trust in Federal Government					0.0391***	0.0388***
					(0.000)	(0.000)
Trust in State Government					-0.0226***	-0.0231***
					(0.001)	(0.001)
Trust in CDC					0.149***	0.149***
					(0.000)	(0.000)
Trust in Pharmaceutical companies					0.0258***	0.0257***
					(0.000)	(0.000)
Trust in Tech companies					0.00160	0.000701
					(0.835)	(0.927)
Frequency of travel						0.0277**
						(0.024)
Constant	-0.0781**	-0.0781**	0.0475	0.0475	-0.918***	-0.923***
	(0.013)	(0.013)	(0.550)	(0.550)	(0.000)	(0.000)
Observations	3639	3639	3489	3489	3461	3461
Adjusted R^2	0.002	0.002	0.220	0.220	0.467	0.467

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

vaccine_status	Freq.	Percent	Cum.
Both doses received	2,277	57.07	57.07
No dose: doesn't want vaccine	368	9.22	66.29
No dose: doubts over vaccine	475	11.90	78.20
No dose: wants vaccine	410	10.28	88.47
One dose: doubts on 2nd	23	0.58	89.05
One dose: intention to get 2nd	431	10.80	99.85
One dose: no intention for 2nd	6	0.15	100.00
Total	3,990	100.00	

Spillover effects on vaccination intention

Table 4.A.17: Determinants of vaccination intention for respondents who have not yet received any dose of the vaccine after the introduction of the pass table

	(1) Vaccination intention	(2) Vaccination intention	(3) Vaccination intention	(4) Vaccination intention	(5) Vaccination intention	(6) Vaccination intention
Status Quo	0.0111	0.0111	-0.0681	-0.0681	0.00432	0.0124
	(0.928)	(0.928)	(0.546)	(0.546)	(0.964)	(0.897)
Peer Effect	-0.265**	-0.265**	-0.239**	-0.239**	-0.124	-0.120
	(0.033)	(0.033)	(0.044)	(0.044)	(0.223)	(0.238)
Peer Effect Status Quo	-0.192	-0.192	-0.178	-0.178	-0.0225	-0.0103
	(0.122)	(0.122)	(0.126)	(0.126)	(0.824)	(0.919)
Age			-0.0189***	-0.0189***	-0.0132***	-0.0123***
			(0.000)	(0.000)	(0.000)	(0.000)
Income			-0.00175	-0.00175	0.00151	-0.00233
			(0.896)	(0.896)	(0.895)	(0.840)
Female			-0.128	-0.128	-0.0798	-0.0673
			(0.129)	(0.129)	(0.270)	(0.357)
White			-0.145	-0.145	-0.111	-0.0918
			(0.130)	(0.130)	(0.183)	(0.275)
Political Scale			-0.240***	-0.240***	-0.141***	-0.138***
			(0.000)	(0.000)	(0.000)	(0.000)
Education			0.101***	0.101***	0.0925***	0.0747**
			(0.003)	(0.003)	(0.002)	(0.014)
In full or part time employment			0.00988	0.00988	-0.0611	-0.0806
			(0.918)	(0.918)	(0.482)	(0.355)
Student			0.573***	0.573***	0.498***	0.479***
			(0.000)	(0.000)	(0.001)	(0.001)
Republican			0.00900	0.00900	0.0487	0.0307
			(0.943)	(0.943)	(0.630)	(0.763)
Trust in Federal Government					0.0460*	0.0451*
					(0.094)	(0.099)
Trust in State Government					-0.0430**	-0.0431**
					(0.042)	(0.042)
Trust in CDC					0.224***	0.226***
					(0.000)	(0.000)
Trust in Pharmaceutical companies					0.0602***	0.0589***
					(0.007)	(0.008)
Trust in Tech companies					-0.0308	-0.0346*
					(0.138)	(0.098)
Frequency of travel						0.0812**
						(0.028)
Constant	3.017***	3.017***	4.246***	4.246***	2.585***	2.557***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1253	1253	1192	1192	1158	1158
Adjusted R^2	0.004	0.004	0.170	0.170	0.400	0.403

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.A.18: Determinants of vaccination intention for respondents who already received the first dose of the vaccine after the introduction of the pass table

	(1) Vaccination intention	(2) Vaccination intention	(3) Vaccination intention	(4) Vaccination intention	(5) Vaccination intention	(6) Vaccination intention
Status Quo	-0.209	-0.209	-0.247*	-0.247*	-0.271*	-0.275*
	(0.152)	(0.152)	(0.085)	(0.085)	(0.062)	(0.059)
Peer Effect	-0.0247	-0.0247	-0.0580	-0.0580	-0.0792	-0.0807
	(0.838)	(0.838)	(0.631)	(0.631)	(0.507)	(0.501)
Peer Effect Status Quo	0.196*	0.196*	0.161	0.161	0.106	0.103
	(0.055)	(0.055)	(0.106)	(0.106)	(0.290)	(0.310)
Age			0.0000167	0.0000167	0.000856	0.000271
			(0.997)	(0.997)	(0.872)	(0.959)
Income			0.0267*	0.0267*	0.0235	0.0243*
			(0.055)	(0.055)	(0.104)	(0.092)
Female			0.242***	0.242***	0.223**	0.213**
			(0.006)	(0.006)	(0.013)	(0.015)
White			0.106	0.106	0.116	0.114
			(0.233)	(0.233)	(0.202)	(0.208)
Political Scale			-0.0885***	-0.0885***	-0.0906***	-0.0905***
			(0.002)	(0.002)	(0.003)	(0.003)
Education			-0.0281	-0.0281	-0.0450	-0.0353
			(0.439)	(0.439)	(0.227)	(0.388)
In full or part time employment			-0.0621	-0.0621	-0.0679	-0.0516
			(0.552)	(0.552)	(0.550)	(0.646)
Student			0.0956	0.0956	0.0781	0.0842
			(0.490)	(0.490)	(0.593)	(0.568)
Republican			-0.219	-0.219	-0.106	-0.0954
			(0.293)	(0.293)	(0.595)	(0.629)
Trust in Federal Government					0.0288	0.0275
					(0.342)	(0.357)
Trust in State Government					-0.0334	-0.0316
					(0.238)	(0.257)
Trust in CDC					0.0307	0.0309
					(0.215)	(0.212)
Trust in Pharmaceutical companies					0.00433	0.00604
					(0.855)	(0.796)
Trust in Tech companies					0.0267	0.0272
					(0.236)	(0.229)
Frequency of travel						-0.0325
						(0.465)
Constant	4.529***	4.529***	4.583***	4.583***	4.375***	4.374***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	460	460	445	445	433	433
Adjusted R^2	0.017	0.017	0.085	0.085	0.097	0.096

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.A.19: Determinants of vaccination intention for respondents who already received both doses of the vaccine after the introduction of the pass table (if a new vaccination cycle is required)

	(1) Vaccination intention	(2) Vaccination intention	(3) Vaccination intention	(4) Vaccination intention	(5) Vaccination intention	(6) Vaccination intention
Status Quo	-0.0523	-0.0523	-0.0184	-0.0184	-0.0302	-0.0304
	(0.263)	(0.263)	(0.693)	(0.693)	(0.497)	(0.494)
Peer Effect	0.000108	0.000108	0.00559	0.00559	0.00849	0.00696
	(0.998)	(0.998)	(0.905)	(0.905)	(0.852)	(0.879)
Peer Effect Status Quo	-0.0504	-0.0504	-0.0176	-0.0176	-0.0231	-0.0258
	(0.291)	(0.291)	(0.714)	(0.714)	(0.613)	(0.572)
Age			0.000666	0.000666	-0.00100	-0.000842
			(0.681)	(0.681)	(0.534)	(0.599)
Income			0.0169^{***}	0.0169^{***}	0.0107^{**}	0.00955^{*}
			(0.001)	(0.001)	(0.033)	(0.062)
Female			0.0438	0.0438	0.0531	0.0536
			(0.208)	(0.208)	(0.117)	(0.114)
White			0.0177	0.0177	0.00951	0.0133
			(0.663)	(0.663)	(0.811)	(0.740)
Political Scale			-0.0871^{***}	-0.0871^{***}	-0.0749^{***}	-0.0747^{***}
			(0.000)	(0.000)	(0.000)	(0.000)
Education			0.0145	0.0145	0.0154	0.0126
			(0.315)	(0.315)	(0.268)	(0.378)
In full or part time employment			-0.0805^{*}	-0.0805^{*}	-0.0841^{**}	-0.0876^{**}
			(0.066)	(0.066)	(0.044)	(0.036)
Student			-0.0323	-0.0323	-0.0828	-0.0864
			(0.621)	(0.621)	(0.191)	(0.173)
Republican			-0.152^{*}	-0.152^{*}	-0.0765	-0.0799
			(0.058)	(0.058)	(0.316)	(0.297)
Trust in Federal Government					0.0137	0.0133
					(0.226)	(0.237)
Trust in State Government					-0.0116	-0.0119
					(0.221)	(0.209)
Trust in CDC					0.0686^{***}	0.0691^{***}
					(0.000)	(0.000)
Trust in Pharmaceutical companies					0.0140	0.0143
					(0.172)	(0.161)
Trust in Tech companies					0.00523	0.00482
					(0.647)	(0.671)
Frequency of travel						0.0182
						(0.254)
Constant	4.706^{***}	4.706^{***}	4.717^{***}	4.717^{***}	4.241^{***}	4.235^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2275	2275	2158	2158	2121	2121
Adjusted R^2	-0.000	-0.000	0.055	0.055	0.115	0.115

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.A.20: Determinants of vaccination intention after the introduction of the pass table (aggregating all vaccination intention answers)

	(1) Vaccination intention	(2) Vaccination intention	(3) Vaccination intention	(4) Vaccination intention	(5) Vaccination intention	(6) Vaccination intention
Status Quo	-0.0942	-0.0942	-0.0692	-0.0692	-0.0553	-0.0535
	(0.115)	(0.115)	(0.213)	(0.213)	(0.262)	(0.279)
Peer Effect	-0.126**	-0.126**	-0.107*	-0.107*	-0.0695	-0.0705
	(0.039)	(0.039)	(0.062)	(0.062)	(0.175)	(0.169)
Peer Effect Status Quo	-0.0978	-0.0978	-0.0501	-0.0501	-0.0318	-0.0331
	(0.106)	(0.106)	(0.368)	(0.368)	(0.522)	(0.505)
Age			-0.0000774	-0.0000774	-0.00176	-0.00126
			(0.968)	(0.968)	(0.320)	(0.475)
Income			0.0341***	0.0341***	0.0213***	0.0186***
			(0.000)	(0.000)	(0.000)	(0.001)
Female			-0.0743*	-0.0743*	-0.0312	-0.0258
			(0.071)	(0.071)	(0.399)	(0.486)
White			0.0115	0.0115	-0.00302	0.00627
			(0.805)	(0.805)	(0.943)	(0.882)
Political Scale			-0.229***	-0.229***	-0.159***	-0.158***
			(0.000)	(0.000)	(0.000)	(0.000)
Education			0.161***	0.161***	0.120***	0.111***
			(0.000)	(0.000)	(0.000)	(0.000)
In full or part time employment			-0.0167	-0.0167	-0.0318	-0.0437
			(0.762)	(0.762)	(0.520)	(0.376)
Student			0.449***	0.449***	0.282***	0.271***
			(0.000)	(0.000)	(0.000)	(0.000)
Republican			-0.339***	-0.339***	-0.155**	-0.163**
			(0.000)	(0.000)	(0.031)	(0.023)
Trust in Federal Government					0.0305**	0.0301**
					(0.013)	(0.014)
Trust in State Government					-0.0257***	-0.0266***
					(0.010)	(0.008)
Trust in CDC					0.178***	0.179***
					(0.000)	(0.000)
Trust in Pharmaceutical companies					0.0600***	0.0599***
					(0.000)	(0.000)
Trust in Tech companies					-0.0310***	-0.0324***
					(0.008)	(0.005)
Frequency of travel						0.0474***
						(0.008)
Constant	4.181***	4.181***	3.910***	3.910***	2.827***	2.818***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3993	3993	3799	3799	3716	3716
Adjusted R^2	0.000	0.000	0.195	0.195	0.357	0.358

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Pairwise comparisons of means with equal variances

over : **group_no**

	Number of Comparisons
group_no	**3**

pass_importance	Contrast	Std. Err.	Dunnett t	Dunnett P>|t|	Dunnett [95% Conf.	Interval]
group_no						
Status Quo vs Control	**.4780176**	**.1498593**	**3.19**	**0.004**	**.1259988**	**.8300364**
Peer Effect vs Control	**.4488686**	**.1500478**	**2.99**	**0.008**	**.0964072**	**.80133**
PE + SQ vs Control	**.6649899**	**.1499722**	**4.43**	**0.000**	**.312706**	**1.017274**

. pwmean pass_preventspread, over(group_no) mcompare(dunnett) effects

Pairwise comparisons of means with equal variances

over : **group_no**

	Number of Comparisons
group_no	**3**

pass_preventspread	Contrast	Std. Err.	Dunnett t	Dunnett P>|t|	Dunnett [95% Conf.	Interval]
group_no						
Status Quo vs Control	**.32639**	**.1521134**	**2.15**	**0.082**	**-.0309235**	**.6837036**
Peer Effect vs Control	**.4444529**	**.1523045**	**2.92**	**0.010**	**.0866903**	**.8022155**
PE + SQ vs Control	**.7871948**	**.1523045**	**5.17**	**0.000**	**.4294323**	**1.144957**

4.A.4 Post-hoc tests: treatments vs control

```
. pwmean pass_normalcy, over(group_no) mcompare(dunnett) effects

Pairwise comparisons of means with equal variances

over         : group_no
```

	Number of Comparisons
group_no	3

pass_normalcy	Contrast	Std. Err.	Dunnett t	Dunnett P>|t|	Dunnett [95% Conf.	Interval]
group_no						
Status Quo vs Control	.4092068	.1514514	2.70	0.019	.0534481	.7649654
Peer Effect vs Control	.395241	.1514898	2.61	0.025	.0393922	.7510898
PE + SQ vs Control	.737457	.1513749	4.87	0.000	.381878	1.093036

```
. pwmean pass_limitliberty, over(group_no) mcompare(dunnett) effects

Pairwise comparisons of means with equal variances

over         : group_no
```

	Number of Comparisons
group_no	3

pass_limitliberty	Contrast	Std. Err.	Dunnett t	Dunnett P>|t|	Dunnett [95% Conf.	Interval]
group_no						
Status Quo vs Control	-.3721272	.1554656	-2.39	0.045	-.7373151	-.0069392
Peer Effect vs Control	.0294156	.1555052	0.19	0.995	-.3358655	.3946967
PE + SQ vs Control	-.3833839	.1563135	-2.45	0.038	-.7505634	-.0162043

```
. pwmean pass_socialfabric, over(group_no) mcompare(dunnett) effects

Pairwise comparisons of means with equal variances

over         : group_no
```

	Number of Comparisons
group_no	3

pass_socialfabric	Contrast	Std. Err.	Dunnett t	P>|t|	Dunnett [95% Conf.	Interval]
group_no						
Status Quo vs Control	-.2797201	.1503161	-1.86	0.155	-.632812	.0733717
Peer Effect vs Control	-.0688592	.1502775	-0.46	0.941	-.4218602	.2841418
PE + SQ vs Control	-.4682747	.1507854	-3.11	0.005	-.8224688	-.1140806

```
. pwmean pass_privacy, over(group_no) mcompare(dunnett) effects

Pairwise comparisons of means with equal variances

over         : group_no
```

	Number of Comparisons
group_no	3

pass_privacy	Contrast	Std. Err.	Dunnett t	P>|t|	Dunnett [95% Conf.	Interval]
group_no						
Status Quo vs Control	-.3241938	.1523358	-2.13	0.086	-.6820299	.0336423
Peer Effect vs Control	-.0403011	.1520241	-0.27	0.987	-.397405	.3168029
PE + SQ vs Control	-.3484439	.1527718	-2.28	0.059	-.7073042	.0104163

```
. pwmean pass_unfair_travel, over(group_no) mcompare(dunnett) effects

Pairwise comparisons of means with equal variances

over         : group_no
```

	Number of Comparisons
group_no	3

pass_unfair_travel	Contrast	Std. Err.	Dunnett t	Dunnett P>|t|	Dunnett [95% Conf.	Interval]
group_no						
Status Quo vs Control	-.2232949	.1530898	-1.46	0.328	-.5829021	.1363123
Peer Effect vs Control	.2153462	.1532478	1.41	0.358	-.1446321	.5753245
PE + SQ vs Control	-.0301113	.1537692	-0.20	0.995	-.3913145	.3310918

```
. pwmean pass_unfair_harmlocals, over(group_no) mcompare(dunnett) effects

Pairwise comparisons of means with equal variances

over         : group_no
```

	Number of Comparisons
group_no	3

pass_unfair_harmlocals	Contrast	Std. Err.	Dunnett t	Dunnett P>|t|	Dunnett [95% Conf.	Interval]
group_no						
Status Quo vs Control	-.1371456	.1448321	-0.95	0.662	-.4773555	.2030643
Peer Effect vs Control	.2254693	.1448321	1.56	0.277	-.1147405	.5656792
PE + SQ vs Control	-.1923754	.1451307	-1.33	0.405	-.5332868	.1485359

```
. pwmean pass_forge, over(group_no) mcompare(dunnett) effects

Pairwise comparisons of means with equal variances

over         : group_no
```

	Number of Comparisons
group_no	3

pass_forge	Contrast	Std. Err.	Dunnett t	Dunnett P>|t|	Dunnett [95% Conf. Interval]	
group_no						
Status Quo vs Control	-.0785678	.1329817	-0.59	0.885	-.3909411	.2338055
Peer Effect vs Control	.0028756	.1330152	0.02	1.000	-.3095765	.3153276
PE + SQ vs Control	-.2136879	.1331498	-1.60	0.254	-.5264562	.0990804

```
. pwmean pass_inducevaccine, over(group_no) mcompare(dunnett) effects

Pairwise comparisons of means with equal variances

over         : group_no
```

	Number of Comparisons
group_no	3

pass_inducevaccine	Contrast	Std. Err.	Dunnett t	Dunnett P>|t|	Dunnett [95% Conf. Interval]	
group_no						
Status Quo vs Control	.0906344	.1259279	0.72	0.813	-.2051696	.3864384
Peer Effect vs Control	.0172356	.1259596	0.14	0.998	-.278643	.3131141
PE + SQ vs Control	.1935194	.1260552	1.54	0.288	-.1025835	.4896224

```
. pwmean pass_flightsinter, over(group_no) mcompare(dunnett) effects

Pairwise comparisons of means with equal variances

over         : group_no
```

	Number of Comparisons
group_no	3

pass_flightsinter	Contrast	Std. Err.	Dunnett t	Dunnett P>|t|	Dunnett [95% Conf.	Interval]
group_no						
Status Quo vs Control	.2059544	.1581997	1.30	0.420	-.1656558	.5775646
Peer Effect vs Control	.2508196	.1584809	1.58	0.265	-.1214513	.6230904
PE + SQ vs Control	.3565106	.1584809	2.25	0.064	-.0157602	.7287815

```
. pwmean pass_intentionalinfection, over(group_no) mcompare(dunnett) effects

Pairwise comparisons of means with equal variances

over         : group_no
```

	Number of Comparisons
group_no	3

pass_intentionalinfec~n	Contrast	Std. Err.	Dunnett t	Dunnett P>|t|	Dunnett [95% Conf.	Interval]
group_no						
Status Quo vs Control	.0168776	.0753055	0.22	0.992	-.1600146	.1937698
Peer Effect vs Control	-.0283784	.0753453	-0.38	0.965	-.2053641	.1486072
PE + SQ vs Control	-.0196794	.0754253	-0.26	0.988	-.196853	.1574943

```
. pwmean pass_proscons, over(group_no) mcompare(dunnett) effects

Pairwise comparisons of means with equal variances

over         : group_no
```

	Number of Comparisons
group_no	3

pass_proscons	Contrast	Std. Err.	Dunnett t	Dunnett P>|t|	Dunnett [95% Conf.	Interval]
group_no						
Status Quo vs Control	.4123174	.1497878	2.75	0.016	.0604666	.7641681
Peer Effect vs Control	.1463275	.1497878	0.98	0.641	-.2055232	.4981782
PE + SQ vs Control	.5137298	.1498259	3.43	0.002	.1617895	.8656701

```
. pwmean f1, over(group_no) mcompare(dunnett) effects

Pairwise comparisons of means with equal variances

over         : group_no
```

	Number of Comparisons
group_no	3

f1	Contrast	Std. Err.	Dunnett t	Dunnett P>|t|	Dunnett [95% Conf.	Interval]
group_no						
Status Quo vs Control	.1188021	.0460448	2.58	0.027	.0106432	.226961
Peer Effect vs Control	.053496	.0459561	1.16	0.510	-.0544547	.1614467
PE + SQ vs Control	.1414529	.0460959	3.07	0.006	.0331738	.2497321

```
. pwmean pass_importance, over(treatments) mcompare(dunnett) effects

Pairwise comparisons of means with equal variances

over         : treatments
```

	Number of Comparisons
treatments	**2**

pass_importance	Contrast	Std. Err.	Dunnett t	Dunnett P>|t|	Dunnett [95% Conf.	Interval]
treatments						
Status Quo vs PE + SQ	**-.1869724**	**.1500105**	**-1.25**	**0.353**	**-.5188154**	**.1448706**
Peer Effect vs PE + SQ	**-.2161213**	**.1501992**	**-1.44**	**0.257**	**-.5483816**	**.1161389**

```
. pwmean pass_preventspread, over(treatments) mcompare(dunnett) effects

Pairwise comparisons of means with equal variances

over         : treatments
```

	Number of Comparisons
treatments	**2**

pass_preventspread	Contrast	Std. Err.	Dunnett t	Dunnett P>|t|	Dunnett [95% Conf.	Interval]
treatments						
Status Quo vs PE + SQ	**-.4608048**	**.1522443**	**-3.03**	**0.005**	**-.7975893**	**-.1240203**
Peer Effect vs PE + SQ	**-.3427419**	**.1524356**	**-2.25**	**0.046**	**-.6799495**	**-.0055344**

```
. pwmean pass_normalcy, over(treatments) mcompare(dunnett) effects

Pairwise comparisons of means with equal variances

over         : treatments
```

	Number of Comparisons
treatments	2

pass_normalcy	Contrast	Std. Err.	Dunnett t	Dunnett P>|t|	Dunnett [95% Conf.	Interval]
treatments						
Status Quo vs PE + SQ	-.3282502	.1511233	-2.17	0.055	-.6625547	.0060542
Peer Effect vs PE + SQ	-.342216	.1511615	-2.26	0.044	-.676605	-.0078269

```
. pwmean pass_limitliberty, over(treatments) mcompare(dunnett) effects

Pairwise comparisons of means with equal variances

over         : treatments
```

	Number of Comparisons
treatments	2

pass_limitliberty	Contrast	Std. Err.	Dunnett t	Dunnett P>|t|	Dunnett [95% Conf.	Interval]
treatments						
Status Quo vs PE + SQ	.0112567	.1564566	0.07	0.996	-.3348457	.3573592
Peer Effect vs PE + SQ	.4127995	.156496	2.64	0.016	.0666098	.7589892

```
. pwmean pass_socialfabric, over(treatments) mcompare(dunnett) effects

Pairwise comparisons of means with equal variances

over         : treatments
```

	Number of Comparisons
treatments	2

pass_socialfabric	Contrast	Std. Err.	Dunnett t	Dunnett P>|t|	Dunnett [95% Conf.	Interval]
treatments						
Status Quo vs PE + SQ	.1885545	.1504126	1.25	0.349	-.144178	.521287
Peer Effect vs PE + SQ	.3994155	.1503742	2.66	0.015	.0667679	.732063

```
. pwmean pass_privacy, over(treatments) mcompare(dunnett) effects

Pairwise comparisons of means with equal variances

over         : treatments
```

	Number of Comparisons
treatments	2

pass_privacy	Contrast	Std. Err.	Dunnett t	Dunnett P>|t|	Dunnett [95% Conf.	Interval]
treatments						
Status Quo vs PE + SQ	.0242501	.1535262	0.16	0.982	-.3153699	.3638702
Peer Effect vs PE + SQ	.3081429	.153214	2.01	0.081	-.0307866	.6470724

```
. pwmean pass_unfair_travel, over(treatments) mcompare(dunnett) effects

Pairwise comparisons of means with equal variances

over         : treatments

-------------------------------
             |    Number of
             |  Comparisons
-------------+-----------------
  treatments |            2
-------------------------------

------------------------------------------------------------------------------------------
                          |                          Dunnett            Dunnett
       pass_unfair_travel |  Contrast   Std. Err.      t    P>|t|    [95% Conf. Interval]
--------------------------+---------------------------------------------------------------
               treatments |
   Status Quo vs PE + SQ  | -.1931835   .1536769    -1.26   0.347    -.533137    .1467699
  Peer Effect vs PE + SQ  |  .2454575    .153834     1.60   0.193   -.0948435    .5857585
------------------------------------------------------------------------------------------

. pwmean pass_unfair_harmlocals, over(treatments) mcompare(dunnett) effects

Pairwise comparisons of means with equal variances

over         : treatments

-------------------------------
             |    Number of
             |  Comparisons
-------------+-----------------
  treatments |            2
-------------------------------

------------------------------------------------------------------------------------------
                          |                          Dunnett            Dunnett
   pass_unfair_harmlocals |  Contrast   Std. Err.      t    P>|t|    [95% Conf. Interval]
--------------------------+---------------------------------------------------------------
               treatments |
   Status Quo vs PE + SQ  |  .0552299   .1458728     0.38   0.901     -.26746    .3779197
  Peer Effect vs PE + SQ  |  .4178448   .1458728     2.86   0.008    .0951549    .7405346
------------------------------------------------------------------------------------------
```

```
. pwmean pass_forge, over(treatments) mcompare(dunnett) effects

Pairwise comparisons of means with equal variances

over         : treatments
```

	Number of Comparisons
treatments	2

pass_forge	Contrast	Std. Err.	Dunnett t	Dunnett P>|t|	Dunnett [95% Conf.	Interval]
treatments						
Status Quo vs PE + SQ	.1351201	.132768	1.02	0.490	-.1585802	.4288204
Peer Effect vs PE + SQ	.2165635	.1328014	1.63	0.180	-.0772106	.5103375

```
. pwmean pass_inducevaccine, over(treatments) mcompare(dunnett) effects

Pairwise comparisons of means with equal variances

over         : treatments
```

	Number of Comparisons
treatments	2

pass_inducevaccine	Contrast	Std. Err.	Dunnett t	Dunnett P>|t|	Dunnett [95% Conf.	Interval]
treatments						
Status Quo vs PE + SQ	-.102885	.1267562	-0.81	0.629	-.3832863	.1775163
Peer Effect vs PE + SQ	-.1762839	.1267881	-1.39	0.279	-.4567557	.1041879

```
. pwmean pass_flightsinter, over(treatments) mcompare(dunnett) effects

Pairwise comparisons of means with equal variances

over         : treatments
```

	Number of Comparisons
treatments	2

pass_flightsinter	Contrast	Std. Err.	Dunnett t	Dunnett P>|t|	Dunnett [95% Conf.	Interval]
treatments						
Status Quo vs PE + SQ	-.1505562	.1585631	-0.95	0.535	-.5013186	.2002061
Peer Effect vs PE + SQ	-.1056911	.1588438	-0.67	0.730	-.4570745	.2456924

```
. pwmean pass_intentionalinfection, over(treatments) mcompare(dunnett) effects

Pairwise comparisons of means with equal variances

over         : treatments
```

	Number of Comparisons
treatments	2

pass_intentionalinfec~n	Contrast	Std. Err.	Dunnett t	Dunnett P>|t|	Dunnett [95% Conf.	Interval]
treatments						
Status Quo vs PE + SQ	.036557	.0747995	0.49	0.842	-.1289094	.2020234
Peer Effect vs PE + SQ	-.008699	.0748389	-0.12	0.990	-.1742526	.1568545

```
. pwmean pass_proscons, over(treatments) mcompare(dunnett) effects

Pairwise comparisons of means with equal variances

over         : treatments
```

	Number of Comparisons
treatments	2

pass_proscons	Contrast	Std. Err.	Dunnett t	Dunnett P>|t|	Dunnett [95% Conf.	Interval]
treatments						
Status Quo vs PE + SQ	-.1014124	.1494077	-0.68	0.721	-.4319219	.229097
Peer Effect vs PE + SQ	-.3674023	.1494077	-2.46	0.026	-.6979117	-.0368929

```
. pwmean f1, over(treatments) mcompare(dunnett) effects

Pairwise comparisons of means with equal variances

over         : treatments
```

	Number of Comparisons
treatments	2

f1	Contrast	Std. Err.	Dunnett t	Dunnett P>|t|	Dunnett [95% Conf.	Interval]
treatments						
Status Quo vs PE + SQ	-.0226508	.04662	-0.49	0.843	-.1257803	.0804786
Peer Effect vs PE + SQ	-.087957	.0465308	-1.89	0.106	-.1908892	.0149753

Chapter 5

Interactions Between Concerns for the Environment and Other Sources of Concern in 31 European Countries

5.1 Introduction

Worries are closely tied to behaviours and personal preferences (Loewenstein et al., 2001; Leiserowitz et al., 2007; Linden et al., 2019). How much people worry about the environment influences whether they adopt pro-environmental behaviours and their support for policies aimed at climate change mitigation (Leiserowitz, 2006; Bouman et al., 2020). In turn, how worried people are about the environment is likely to depend on how worried they are about other issues, like the state of the economy (Whitmarsh, 2011; Scruggs and Bengal, 2012). Thus, it is important to understand how concerns for the environment interact with other sources of concerns.

There are two main theories that aim to explain the interaction among different sources of worries: the "finite-pool-of-worry" (FPW) hypothesis (Weber, 1997; Hansen, 2004), and the affect generalisation theory (AGT) (Johnson and Tversky, 1983). The FPW hypothesis moves from the observation that humans face cognitive resources constraints (Simon, 1957), and hence they can only have a finite pool of worries (Shome and Marx, 2009). Directly testing the existence of a finite pool of worries would require measuring the overall level of worry across all possible sources of concern over time. This is unlikely to be feasible, so the empirical literature operationalises the FPW theory somewhat differently, and equates it with the idea that if people become more worried about one issue they will be less concerned about something else (Hansen et al., 2004; Sisco, 2020; Evensen et al., 2021). Instead, the AGT posits that concerns over one potential threat can be transferred to other worries via associative networks. Consequently, an increased level of worry about one potential threat would induce a person to worry more about related threats.

Studying how concerns for the environment interact with other sources of concern is complicated by three factors. First, the relationships are mediated by exogenous and endogenous factors, and hence are likely to change over time. Second, directly asking about the relationship among sources of worries is unlikely to produce reliable answers, as people might not be aware of how sources of concern interact in their mind. Third, interactions can be asymmetric. For instance, a growth in the worry for the environment might favour the growth of concerns for the economy, whereas an increase in the concerns for the economy might push down concerns for the environment. Against this background, it is unsurprising that, despite the obvious practical relevance of the research question, there are only a few studies analysing how different concerns interact over time (Sisco, 2020; Evensen et al., 2021).

To fill this gap, we collect data on personal worries in 31 countries between 2012–2019 from the Eurobarometer (2021), the polling instrument of the European Union. We account for all possible answers, and aggregate them in the following categories of concerns: Environment, Safety, Economy, Immigration, and Social issues (see Table 5.2).

To identify the dynamic interactions among these categories of concerns, and - hence to detect instances of AGT and FPW - we adopt the competition model introduced in Marasco et al. (2016). This type of Lotka-Volterra model presents three fundamental advantages. First, it can capture all the possible kinds of interactions among an arbitrarily large number of worries (see Table 5.1) and thus detect instances of AGT and FPW. Second, the model can identify how the kind and the intensity of these interactions evolve over time. Third, since the analytic solutions of the model are known, the interaction coefficients – and hence the existing interactions among worries – can be determined using a limited number of observations.

In our framework, three kinds of interactions fit within the FPW: pure competition, predator-prey (the effect of the predator-worry on the prey-worry), and amensalism. When two sources of worry are in pure competition an increase in one worry pushes down the other. Similarly, when the concerns for the predator-worry increase, the concerns for the prey-worry are pushed down. The same interaction exists in amensalism from one worry to the other. These dynamics are consistent with how the empirical literature operationalises the finite pool of worry hypothesis (Sisco, 2020; Evensen et al., 2021), and therefore we label them “FPW interactions”.

Interaction	Description of the interaction	AGT & FPW
pure competition	the competing worries A and B suffer from each other's existence	FPW from A to B and from B to A
predator-prey	predator-worry (A) benefits from prey-worry (B). Prey-worry suffers from predator-worry	FPW from A to B. AGT from B to A
mutualism	symbiosis or a win-win situation between worries	AGT from A to B and from B to A
commensalism	one worry (B) is positively affected by the other (A), while the other (A) is not affected by the first worry (B)	AGT from A to B
amensalism	one worry (B) is negatively affected by the other (A), while the other (A) is not affected by the first worry (B)	FPW from A to B
neutralism	no interaction	No AGT or FPW

Table 5.1: The possible interactions between pairs of worries

Similarly, three kinds of interactions fit within the AGT: mutualism, predator-prey (the effect of the prey-worry on the predator-worry), and commensalism. When two sources of worry are in a mutualistic relationship an increase in one worry favours the growth of the other. Similarly, an increase in the concern for the prey-worry favours the growth of the predator-worry. The same interaction exists in commensalism from one worry to the other. These dynamics are consistent with how the empirical literature operationalises the affect generalisation theory, and therefore we label them "AGT interactions".

In our modelling framework, FPW interactions from worry A to B emerge when the interaction coefficient of B g_B is positive or when $g_B = 0$ and $g_A > 0$. On the contrary, AGT interactions occur when g_B is negative or when $g_B = 0$ and $g_A < 0$ (see Table 5.3). Then, in contrast of the established literature, identifying the emergence of the FPW and AGT interactions is extremely easy.

The FPW hypothesis and the AGT have previously been portrayed as mutually exclusive (Sisco, 2020), but our modelling framework suggests that they can coexist in three instances. First, when two sources of worry are in a predator-prey relationship the dynamic that emerges is consistent with the FPW hypothesis from the predator-worry to the prey-worry, and simultaneously consistent with the AGT from the prey-worry to the predator-worry. This is because predator-prey is an *asymmetric interaction*, in which the effect of the predator-worry on the prey-worry is of the opposite sign to the effect of the prey-worry on the predator-worry (Dominioni et al., 2020).

Second, the kind of interactions among worries changes over time and across countries.

Thus, it is possible that a pair of worries is in FPW interactions for a period (and/or a country) and in AGT interactions for another. Third, for a given time interval if there are multiple worries it is possible that some worries stand in FPW interaction, whereas other stand in AGT interactions.

5.2 Methods

5.2.1 Data collection and aggregation, the logit model

The analysis is based on the public opinion data on personal worries collected by the *Eurobarometer* between 2012-2019. We consider all the 31 countries for which complete data is available. Each European Barometer survey consisted of approximately 1000 face-to-face interviews per country. As we are interested in personal worries, we focus on the question "*Personally, what are the two most important issues you are facing at the moment? (max. 2 answers)*". The data is reported in terms of percentages of people who indicated a given worry.

The possible answers to the question were: *(i) crime, (ii) the economic situation, (iii) rising prices/ inflation/ cost of living, (iv) taxation, (v) unemployment, (vi) terrorism, (vii) housing, (viii) the financial situation of your household, (ix) immigration, (x) health and social security, (xi) the education system, (xii) the environment, climate and energy issues, (xiii) pensions, (xiv) working conditions, (xv) living conditions, (xvi) defence/ foreign affairs, (xvii) other, (xviii) none, and (xix) don't know.* We consider all possible answers that were included in the years considered (see the Appendix). We aggregate all worries in five categories, and consider the answers *other, none and don't know* as a residual category (see Table 5.2). To statistically support our grouping into categories we carried out a factor analysis both exploratory (to identify the hidden factors) and confirmatory (to validate the proposed clusterization). However, all the tests we carried out confirmed that the data matrix is not factorizable. For instance, the Kaiser-Meyer-Olkin value for the data aggregated at EU level is 0.393, which is much below the acceptable level (Watkins, 2018). Similarly, the dataset fails also the Haitovsky multicollinearity test. This was not surprising as the data from the Eurobarometer gives us only aggregated data, making the number of observations lower than the parameters that need to be estimated

Let $W_{i,j}(t)$ be the total number of respondents in the $j-th$ country that at time t indicated a worry included in the $i-th$ category, i.e.

Category	Issues
Environment	environment, climate and energy issues
Safety	crime, terrorism
Economy	economic situation, rising prices/ inflation/ cost of living, taxation, unemployment, the financial situation of your household, pensions, working conditions
Immigration	immigration
Social issues	health and social security, the education system, living conditions, housing
Outside option	other, none, don't know

Table 5.2: Aggregation of worries in categories

$$W_{i,j}(t) = \sum_{h_i=1}^{n_i} w_{h_i,j}(t), \quad i = 0, ..., 5, \quad j = 1, ..., 31 \tag{5.1}$$

where $w_{h_i,j}$ is the number of respondents indicating the worry h_i belonging to the $i-th$ category, and n_i is the number of worries of the $i-th$ category for the $j-th$ country.

Then, the shares $P_{i,j}(t)$ at time t for the categories Environment ($i = 1$), Safety ($i = 2$), Economy ($i = 3$), Immigration ($i = 4$), Social issues ($i = 5$), and Outside option ($i = 0$) for the $j-th$ country are determined as follows.

$$P_{i,j}(t) = \frac{W_{i,j}(t)}{\sum_{h=0}^{5} W_{h,j}(t)}, \quad i = 0, ..., 5, \quad j = 1, ..., 31. \tag{5.2}$$

We identify the shares $P_{i,j}(t)$ with the probability of choosing the category i from all possible categories via the *logit model*, i.e.

$$P_{i,j}(t) = \frac{\exp(f_{i,j}(t))}{\sum_{h=0}^{5} \exp(f_{h,j}(t))}, \quad i = 0, ..., 5, \quad j = 1, ..., 31 \tag{5.3}$$

where $f_{i,j}(t)$ is the *utility function* for a respondent of $j-th$ country to choose a worry in the $i-th$ category at time t. In particular, each utility function $f_{i,j}(t)$ is defined as a (linear or nonlinear) function of all aspects and attributes impacting the choice among alternative worries. Furthermore, since the category *Outside option* ($i = 0$) plays the role of the *outside good*, then Eq. (5.3) becomes

$$
\begin{aligned}
P_{i,j}(t) &= \frac{\exp(f_{i,j}(t))}{1 + \sum_{h=1}^{5} \exp(f_{h,j}(t))}, \quad i = 1, \ldots, 5, \quad j = 1, \ldots, 31 \\
P_{0,j}(t) &= \frac{1}{1 + \sum_{h=1}^{5} \exp(f_{h,j}(t))},
\end{aligned} \tag{5.4}
$$

where $P_{0,j}(t) = 1 - \sum_{i=1}^{5} P_{i,j}(t)$ at any time t.

Dynamical competition model of Lotka-Volterra type

Assuming that all the utility functions $f_{i,j}(t)$ are of class $C^2([t_0, +\infty))$, it can be proved that Eqs. $(5.4)_1$ are the unique (global) solution of the following Cauchy problem

$$
\begin{cases}
\dfrac{dP_{i,j}(t)}{dt} = g_{i,j}(t) P_{i,j}(t) [1 - P_{i,j}(t)] - \displaystyle\sum_{h=1, h \neq i}^{5} g_{h,j}(t) P_{h,j}(t) P_{i,j}(t), \quad i = 1, \ldots, 5, \\
P_{i.j}(t_0) = \dfrac{\exp(f_{i,j}(t_0))}{1 + \sum_{h=1}^{5} \exp(f_{h,j}(t_0))} \qquad\qquad t \in [t_0, +\infty)
\end{cases} \tag{5.5}
$$

where $g_{i,j} = df_{i,j}/dt$ and $j = 1, \ldots, 31$.

For each country, the share $P_{i.j}(t)$ of the $i-th$ category increases when its utility function $f_{i.j}(t)$ increases, whereas it decreases when the utility function $f_{h.j}(t)$ of any other category increases. Thus, owing to Eq. (5.5), the evolution of the share $P_{i.j}(t)$ of the $i-th$ category for the $j-th$ country is mathematically determined by the intrinsic growth rate function $g_{i.j}(t)$ and the competition functions $g_{h.j}(t)$ between the $i-th$ and $h-th$ categories. Then, at any time and for any given country, the competitive interactions between any pair of categories – and therefore the presence of AGT and FPW interactions, or both – are determined by the signs of the functions $g_{i.j}(t)$ according to Table 5.3.

Furthermore, owing to Table 5.3, except for when amensalism or commensalism may occur, the AGT and FPW interactions between all worry categories $P_{i,j}$ and a fixed category $P_{h,j}$, for all $i \neq h$, only depend on sign of the interaction coefficient $g_{h,j}$ (see Appendix).

To determine the utility functions – and hence the interactions coefficients – from the

$g_{i,j}$	$g_{h,j}$	**Type of interaction**	$P_{i,j} \longrightarrow P_{h,j}$	$P_{h,j} \longrightarrow P_{i,j}$
+	+	pure competition	**FPW**	**FPW**
−	+	predator–prey	**FPW**	**AGT**
+	0	amensalism	**FPW**	⁄
−	−	mutualism	**AGT**	**AGT**
+	−	prey–predator	**AGT**	**FPW**
−	0	commensalism	**AGT**	⁄
0	0	neutralism	⁄	⁄

Table 5.3: The competitive roles between any pair of categories $P_{i,j}(t)$ and $P_{h,j}(t)$ for the $j-th$ country and their relationships with FPW and AGT interactions.

historical data of the categories of worry we first determine a discrete set of values for each of them as follows

$$f_{i,j}(t) = \ln P_{i,j}(t) - \ln P_{0,j}(t), \quad \forall i,j \tag{5.6}$$

then we use a Fourier series of order n to obtain an approximate analytical form of these functions.

In Figs. 5.1-5.3, as an example, we present the results of our model for Germany. The results for all the countries can be found in the Appendix.

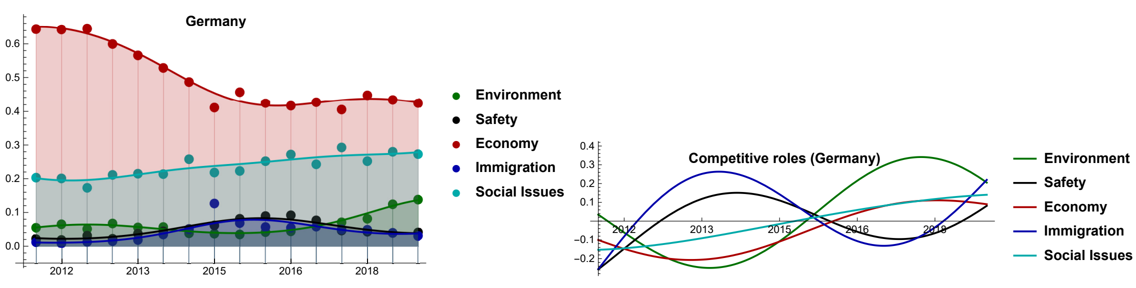

Figure 5.1: (left) Observed (point) and estimated (continuous line) category shares; (right) competitive roles of all worries over the period 2012 – 2019 for the Germany.

Fig. 5.1 (right panel) shows the simultaneous interactions among all sources of worries, whereas Fig. 5.A.1 highlights how the category environment interacts with each of the other categories.

In Fig. 5.3 we show AGT and FPW interactions of Environment versus Safety and Economy and vice versa for the Germany in the time interval 2012 – 2019. We assess the accuracy of our model using the mean square error (MSE) and we found that for all countries and categories, the order of magnitude of the MSE is between 10^{-6} and 10^{-4} (see Appendix).

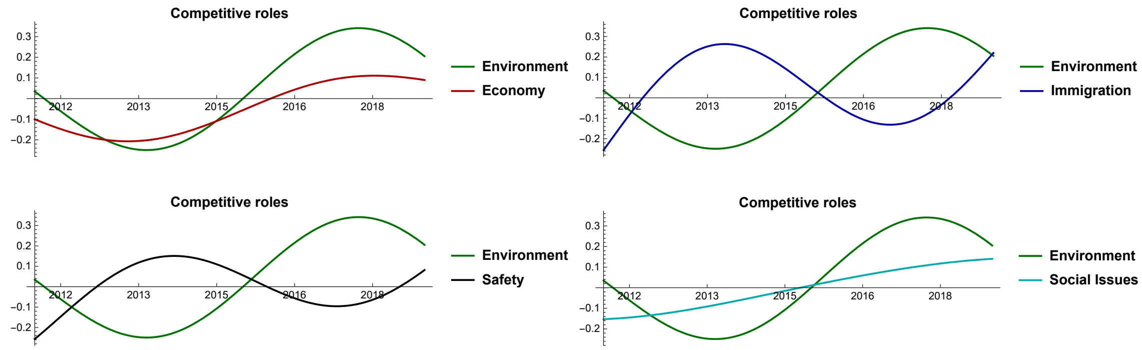

Figure 5.2: Competitive roles of Environment versus Economy, Immigration, Safety, and Social issues, respectively, for Germany in the time interval $[2012, 2019]$.

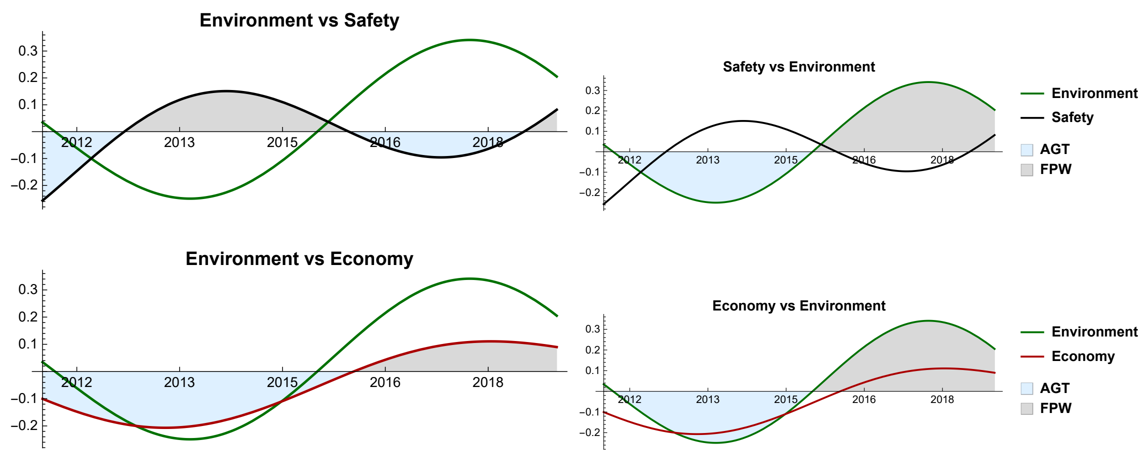

Figure 5.3: AGT and FPW interactions of Environment versus Safety and Economy, and vice versa over the time period 2012 – 2019.

5.2.2 Statistical tests

We use the paired t-test to assess whether *(i)* the averages of the relative frequency distributions of AGT and FPW among the concerns differ; *(ii)* the averages of the relative frequency distributions of AGT between any pairs of concerns, e.g., Environment vs Economy and Environment vs Safety, differ.

Let $data_1$ and $data_2$ be a paired samples of equal length $n = 31$. After verifying that the differences distribution $data_1 - data_2$ forms a sample from a normal population, we test whether the mean of $data_1 - data_2$ is zero using the Student paired t-test. In detail, we test the null hypothesis $H_0 : \mu_{12} = \mu_0$ against the alternative hypothesis $H_0 : \mu_{12} \neq \mu_0$, where μ_{12} is the mean of the paired differences of the two data sets $data_1 - data_2$ and $\mu_0 = 0$. The test statistic is assumed to follow a Student distribution, and the null hypothesis H_0 is rejected only if $p < \alpha$, where the significance level α is set to 0.05.

We find that the null hypothesis H_0 is rejected in all cases except for the averages of the relative frequency distributions of AGT and FPW for Environment vs Safety (see Appendix).

5.3 Results

5.3.1 Finite Pool of Worry and Affect Generalisation Theory coexist

First, we investigate whether FPW and AGT can simultaneously coexist within a given pair of worries. In our framework, this condition is realised when two worries are in a predator-prey interaction, i.e., when the interaction coefficients have opposite signs. In fact – consistently with the FPW hypothesis – an increase in the worry-predator pushes down the worry-prey, while – consistently with the AGT – an increase in the worry-prey favours the growth of the worry-predator.

Figure 5.4 indicates how often predator-prey relationships emerge between the various categories of worries on average across all countries. We observe that predator-prey interactions represent on average about 36% of the total interactions across all countries in all time periods. Moreover, we note that for all pairs of worries there are at least some instances in which AGT and FPW simultaneously coexist.

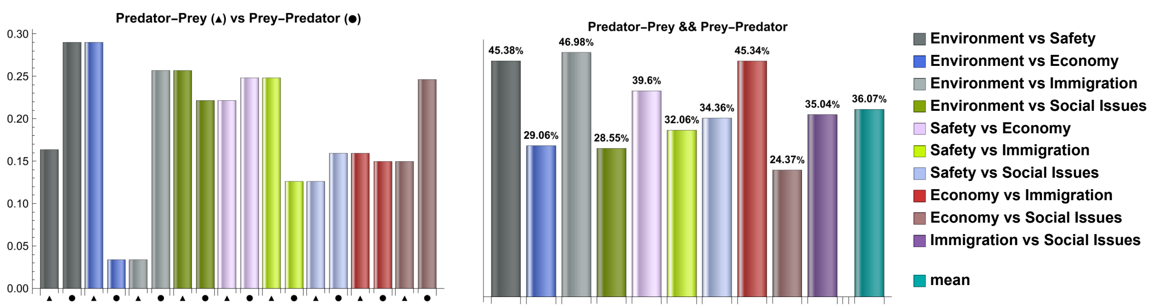

Figure 5.4: The relative frequency distributions of the coexistence of AGT and FPW (asymmetric interactions) for all pair of worries over all countries in the time interval $[2012, 2019]$ (evaluated with a time step of 10^{-3})

Second, we analyse whether the FPW hypothesis and the AGT alternate over time for a given pair of worries. To put it differently, we study if the kind of interaction among worries changes over time. As an example, in Fig. 5.5 we show how interactions consistent with FPW and AGT alternate over time in Denmark, Finland, France, Germany and United Kingdom. We observe that in all countries considered AGT and FPW interactions alternate for all pairs of worries. Third, Fig. 5.5 also shows that at a given moment there can be a pair of worries standing in an interaction that is consistent with one theory (e.g., AGT), while another pair stands in an interaction that is consistent with the other theory (e.g., FPW).

These results suggests that AGT and FPW cannot be portrayed as mutually exclusive when there are multiple sources of worries interacting in people's mind, and the way in which these worries interact changes over time.

5.3.2 The relationship between concerns about the economy and the environment

A large body of literature has investigated the relationship between the economy and the environment (Tiba and Omri, 2017). For instance, an influential strand of literature emphasises that – among other things – ecological limits place inescapable constrains on future economic growth, and therefore that countries should aim at managing economic degrowth (Kallis et al., 2012). This literature reinforces the idea that there is a crucial relationship between the economy and the environment, which is why we focus our attention mostly on this relationship. However, fewer studies investigate how people *perceive* this relationship. And yet this question is extremely relevant. First, concerns for the environment influence private actions (Bouman et al., 2020), which in turn can have a significant impact on climate change (Dietz et al., 2009). One key problem is that the effect on pro-environmental behaviours of extrinsic incentives is generally short-lived (Van Der Linden, 2015). Instead, if people internalise that being concerned about the environment and acting accordingly is the right thing to do, then pro-environmental behaviours are more likely to be sustained over time (Van Der Linden, 2015). Second, it is harder to implement policies to protect the environment and mitigate climate change if people are not concerned about global warming or the environment in general. "To put it differently, it is people who are the drivers of, are affected by, and have the capacity to respond to global change" (Weaver et al., 2014).

Turning to studies investigating the relationship between concerns for the environment and the economy, Whitmarsh (2011) observed that between 2003 and 2008 the perceived severity of climate change sharply declined. She attributed this effect to the looming financial crisis, thus suggesting that increased concerns about the economic situation might have decreased the concerns about climate change. Similarly, Scruggs and Bengal (2012) found that short term economic concerns – and especially unemployment – have a strong chilling effect on climate concerns.

Given the importance of this relationship, and the limited number of studies on the issue, we start by analysing the impact of changes in concerns for the economy on concerns for the

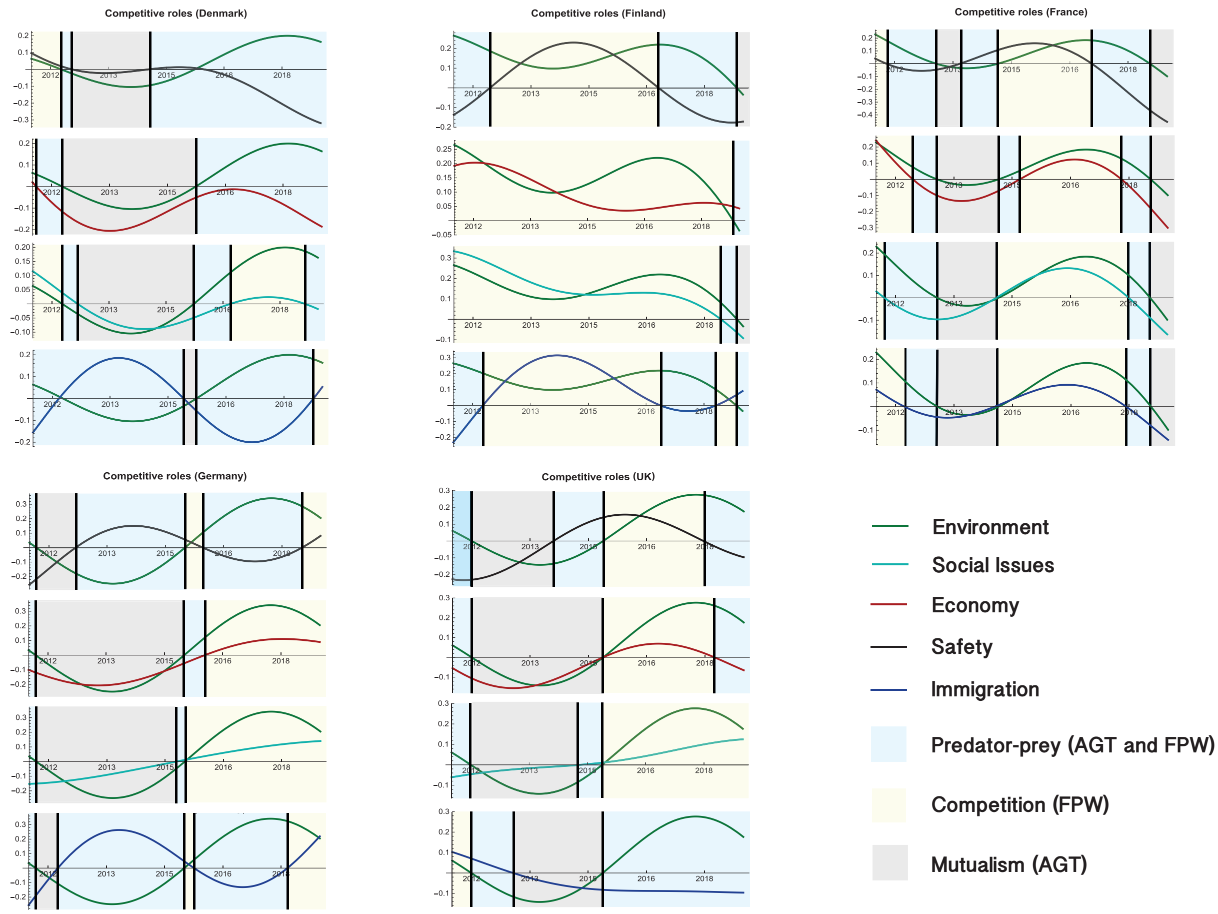

Figure 5.5: Existing interactions of concerns for the environment with concerns for (from top to bottom): safety, economy, social issues and immigration. It refers to Denmark (top left), Finland (top centre), France (top right), Germany (bottom left) and UK (bottom centre). The colour of the background indicates the kind of interaction between a pair of worries: yellow denotes pure competition (FPW), grey denotes mutualism (AGT) and blue denotes predator-prey (AGT and FPW) interactions.

environment. We find that across all countries FPW interactions emerge 60.6% of the time, whereas AGT interactions only emerge 39.4% of the time. Thus, FPW interactions are almost 54% more frequent than AGT interactions (Fig. 5.6, right panel). This difference is statistically significant ($t = -3.3977$, $p = 0.0019$).

On the contrary, when focusing on the impact of changes in concerns for the environment on concerns for the economy we observe a prevalence of AGT interactions. On average, across the 31 countries considered AGT interactions emerge 61.7% of the times, whereas evidence for the FPW interactions emerge 38.3% of the times. Thus AGT interactions are approximately 61% more frequent (Figure 5.6, left panel). This difference is statistically significant (paired t-test: $t = 3.4392$, $p = 0.0017$).

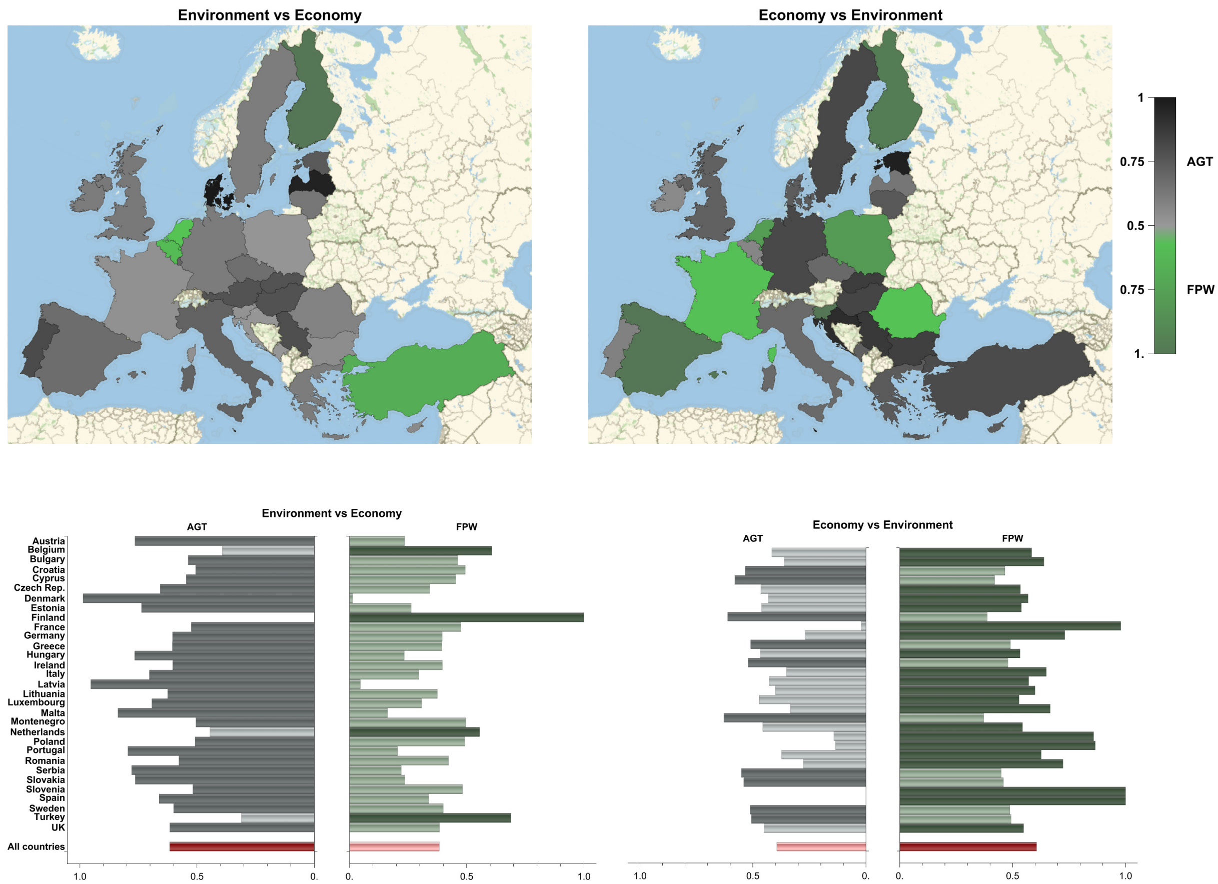

Figure 5.6: The relative frequency distributions of AGT and FPW interactions when studying the impact of concerns for the Environment on concerns for the Economy (left panels) and vice versa (right panels), for each country over the period 2012-2019 with a time step of 10^{-3}. In the lower panels, dark grey and dark green denote a percentage greater than 50% for the AGT and FPW interactions, respectively.

We then turn to the single countries. We observe that when looking at the effect of concerns for the economy on concerns for the environment FPW interactions are more common in 21 countries (approximately 68%) (Fig. 5.6, right panel). Vice versa, in 27 out of 31 countries (approximately 87%) AGT interactions are more common than FPW interactions when considering the effect of concerns for the environment on concerns for the economy (Fig. 5.6, left panel).

Taken together, these results suggest that the AGT is predominant when focusing on the effect of concerns for the environment on concerns for the economy. Therefore, it seems that people have internalised the economic consequences of environmental issues, and consequently concerns for the environment often favour the growth of concerns for the economy. However, our results also suggest that an increase in concerns for the economy pushes down a less immediate concern like the one for the environment. This result is consistent with the findings of Whitmarsh (2011) and Scruggs and Bengal (2012).

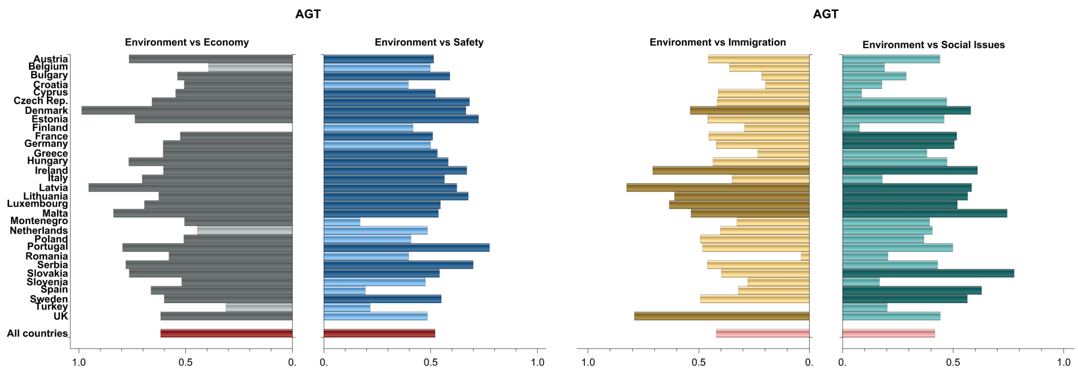

Figure 5.7: The relative frequency distributions of AGT interactions when studying the impact of concerns for the Environment on the other concerns, for each country over the period 2012-2019 with a time step of 10^{-3}. In all panels, dark colours indicate a percentage greater than 50% for AGT interactions.

5.3.3 The effect of concerns for the environment on other worries

Many studies have investigated the relationship between climate change and migratory dynamics. As the problems caused by climate change worsen, more people are displaced and migratory fluxes increase (Kaczan and Orgill-Meyer, 2020; Cattaneo et al., 2020). These dynamics suggest that AGT interactions should be predominant when analysing the effect of concerns for the environment on concerns for immigration. However, we observe that AGT interactions from the environment to immigration are less common than FPW interactions (paired t-test: $t = -2.3917$, $p = 0.0232$). This pattern holds also when looking at single countries. Looking at the effect of concerns for the environment on concerns for immigration FPW interactions are more frequent in 24 countries (approximately 77%) (Fig. 5.7, centre right panel).

Thus, despite the connection between climate change and migratory dynamics identified by the literature (Kaczan and Orgill-Meyer, 2020; Cattaneo et al., 2020), people do not perceive the existence of a linked faith between these issues.

Moreover, many studies have identified a link between environmental factors and safety. In fact, there is robust evidence that warmer temperatures are associated with higher rates of offending and more police calls for service (McDowall et al., 2012; Mares and Moffett, 2019), and that warming global temperatures are associated with a variety of crime measures (Hsiang et al., 2013). Thus, also in this case it would be reasonable to expect a predominance of AGT interactions when considering the effect of concerns for the environment on concerns for safety. Indeed, we do observe a predominance of AGT interactions overall (52%) and in terms of countries (19 or 61.2% of the countries) (Figure 5.7, centre left panel). We note, however, that this difference in the type of interaction is not statistically significant (paired t-test: $t = 0.7844$, $p = 0.4389$).

Last, there could be a relationship between concerns for the environment and social issues because people might prefer investing public resources for social issues, instead of supporting climate-friendly policies. This might be especially true when investments in social issues generate immediate benefits (e.g., healthcare) (Andor et al., 2018). Against this background, one would expect FPW interactions to be predominant. We observe that FPW interactions arise 58% of the times (Fig. 5.7, right panel), while AGT interactions only emerge 42% of the times (paired t-test: $t = -2.4904$ and $p = 0.0185$). FPW interactions are also predominant at the country level (20 countries, or 64.5%).

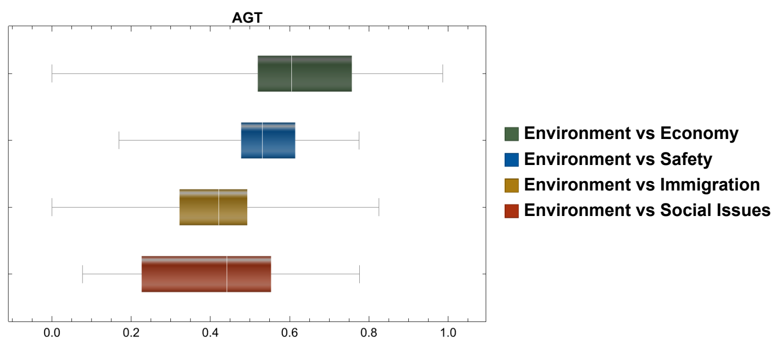

Figure 5.8: Box-and-whisker summary of the frequency distributions of AGT interactions when studying the impact of concerns for the Environment on the other concerns in all countries

5.3.4 Comparing the Environment-Economy relationship with the relationship of Environment with the other categories of worry

We test whether there is a significant difference in how often AGT interactions emerge from the environment to the economy and from the environment to the other categories of worry. We find that AGT interactions emerge more frequently when looking at the effect of the environment on the economy (61.7%), then when looking at the effect of the environment on immigration (paired t-test: $t = 5.8655$, $p = 2.0316 \cdot 10^{-6}$), safety concerns (paired t-test: $t = 3.2088$, $p = 0.0032$) and social issues (paired t-test: $t = 7.1664$, $p = 5.7 \cdot 10^{-8}$) (see Fig. 5.8 and Appendix).

5.3.5 The effect of other concerns on concerns for the environment and the economy

Last, we compare how the other categories of worry influence concerns for the environment and for the economy. We find that the influence of other worries on concerns for the economy is dominated by AGT interactions (61.7%), whereas the effect of other worries on the environment is dominated by FPW interactions (60.6%). Hence AGT is more frequent when focusing on the impact of other worries on concerns for the economy than on concerns for the environment (paired t-test: $t = 6.4521$, $p = 3.97 \cdot 10^{-7}$)

This finding is not surprising. It is reasonable that an increase in concerns like immigration or safety might make people more worried about their economic situation. Vice versa, a person concerned about safety might be less focused on concerns on the environment. Thus, this seems to suggest that economic concerns are a concern of a higher order than environmental concerns. This hypothesis is supported by the interactions that characterise other worries. In fact, the only other worry towards which interactions are dominated by AGT is safety (52.1%), while interactions towards social issues and immigration are dominated by FPW (58.2% and 57.9% respectively).

Building on Maslow's famous pyramid of needs (Maslow, 2012), one could summarise visually our results using a pyramid of worries (Fig. 5.9 and Supplementary Figure 1). We build the pyramid as follows. At the bottom we place economy because it is the worry that is most often in FPW interactions with other worries. Thus, a growth in concerns for the economy often pushes down the other concerns. We place personal safety just above economy because after economy it is the worry that stands more often in FPW interactions with other worries. We then continue until we reach environment, which sits at the very top of the pyramid because it is the worry that is less often in FPW interactions with other worries. We consider economy and personal safety tier 1 worries, because they are more often in FPW interactions than in AGT interactions towards other worries. Therefore, an increase in the level of concern for these tier 1 worries is likely to push down other concerns. To put it differently, tier 1 worries generally overtake other worries. Instead, at the top of the pyramid there are immigration, social issues and environment, which are worries that are more often in AGT interactions than in FPW interactions towards other worries (tier 2 worries). Thus, an increase in the level of concerns for a tier 2 worry is likely to increase the level of concern also for other worries.

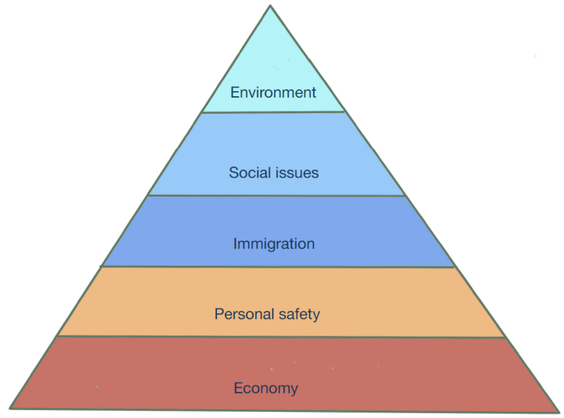

Figure 5.9: The pyramid of worries representing tier 1 worries (Economy and Safety) and tier 2 worries (Immigration, Social Issues and Environment)

Our results refer to the average respondent in the 31 countries considered, and hence it is possible that for subgroups of the population the hierarchy of worries is different. For instance, younger generations might consider environmental concerns a more pressing issue than older generations.

5.4 Conclusions

In this paper we show that the two leading theories explaining how worries are related can coexist. Specifically, we find that AGT dominates the interactions from the environment to the economic situation, suggesting that on average an increase in the concerns for the environment favours the growth of concerns for the economy. Instead, we find that the economic situation is more often in a FPW relationship with concerns for the environment, suggesting that an increase in concerns for the economy pushes down concerns for the environment. In the same vein, we find that immigration and social issues offer often push down concerns for the environment.

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5.A Appendix

5.A.1 Data collection

The Eurobarometer collected answers to the question "*Personally, what are the two most important issues you are facing at the moment? (max. 2 answers)*" from 2009, twice per year, in Spring and in Autumn. In order to use this dataset we had to address three issues. First, in spring 2019 the share of responses for the answer "rising prices/inflation" is missing. Additionally, the sum of all possible answers is less than 1. Given that in all other years the sum is equal to 1 - and that data represents percentages - we assume that Eurobarometer mistakenly omitted to report the percentage of people who indicated rising prices and inflation as one of their main concerns in 2019. For this reason, in 2019 we consider the share for rising prices/inflation as a residual, and impute a value that ensures the sum of all the shares is equal to 1. Second, the worries included in the list of possible answers changes over time. For instance, "defence/foreign affairs" was only included in the three surveys conducted between 2009 and 2010. As in those years the sum of the answers is approximately equal to 1, we assume that the Eurobarometer intentionally excluded this answer from the surveys. For this reason, we assign a value of 0 to these worries in the years in which they are missing. Third, in 2014 and 2015 the Eurobarometer conducted three surveys instead of two, adding an observation in February to the Spring and Autumn one. We discard the February observations to ensure comparability across years, i.e., to ensure that for each year we consider the same number of surveys conducted in the same period of the year.

5.A.2 Accuracy of the model: MSE

To describe average model-performance we rely on the *mean square error (MSE)*

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(h_i - p_i)^2\,,$$

where h_i and p_i are the historical and predicted values, respectively.

In the following table we report the MSE for all countries and categories.

Country	Environment	Safety	Economy	Immigration	Social issues
	MSE				
Austria	1.165×10^{-4}	7.492×10^{-5}	5.075×10^{-4}	9.103×10^{-5}	2.310×10^{-4}
Belgium	3.350×10^{-5}	8.646×10^{-5}	1.438×10^{-4}	3.836×10^{-5}	1.836×10^{-4}
Bulgary	1.550×10^{-5}	3.306×10^{-5}	1.886×10^{-4}	1.723×10^{-5}	1.619×10^{-4}
Croatia	1.837×10^{-5}	2.021×10^{-5}	2.277×10^{-4}	1.352×10^{-5}	8.846×10^{-5}
Cyprus	7.807×10^{-6}	$3.756\text{Ö} \times 10^{-5}$	4.495×10^{-4}	1.627×10^{-5}	1.610×10^{-4}
Czech Rep.	1.301×10^{-5}	2.555×10^{-5}	1.747×10^{-4}	6.914×10^{-5}	1.587×10^{-5}
Denmark	1.378×10^{-4}	7.456×10^{-5}	1.695×10^{-4}	7.366×10^{-5}	2.238×10^{-4}
Estonia	1.126×10^{-5}	1.899×10^{-5}	2.042×10^{-4}	5.852×10^{-5}	7.837×10^{-5}
Finland	1.097×10^{-4}	2.000×10^{-5}	2.338×10^{-4}	4.432×10^{-5}	3.137×10^{-4}
France	1.642×10^{-5}	5.496×10^{-5}	3.009×10^{-4}	7.065×10^{-6}	1.600×10^{-4}
Germany	5.372×10^{-5}	4.685×10^{-5}	2.485×10^{-4}	2.696×10^{-4}	2.437×10^{-4}
Greece	9.497×10^{-6}	2.718×10^{-5}	2.590×10^{-4}	8.327×10^{-6}	1.228×10^{-4}
Hungary	1.276×10^{-5}	6.917×10^{-5}	2.179×10^{-4}	5.092×10^{-5}	1.308×10^{-4}
Ireland	1.620×10^{-5}	9.929×10^{-5}	1.969×10^{-4}	1.636×10^{-5}	2.372×10^{-4}
Italy	1.787×10^{-5}	4.526×10^{-5}	8.440×10^{-5}	2.806×10^{-5}	1.440×10^{-4}
Latvia	6.643×10^{-6}	4.305×10^{-6}	2.580×10^{-4}	1.0671×10^{-5}	7.921×10^{-5}
Lithuania	6.274×10^{-6}	4.644×10^{-6}	2.496×10^{-4}	3.307×10^{-6}	1.376×10^{-4}
Luxembourg	1.454×10^{-4}	5.898×10^{-5}	2.818×10^{-4}	4.391×10^{-5}	2.618×10^{-4}
Malta	1.703×10^{-4}	2.169×10^{-4}	4.127×10^{-4}	1.458×10^{-4}	2.888×10^{-4}
Montenegro	1.223×10^{-4}	1.359×10^{-4}	5.042×10^{-4}	1.203×10^{-5}	1.072×10^{-4}
Netherlands	6.671×10^{-5}	2.780×10^{-5}	1.527×10^{-4}	4.484×10^{-5}	7.640×10^{-5}
Poland	9.551×10^{-6}	3.658×10^{-5}	9.604×10^{-5}	1.234×10^{-5}	9.569×10^{-5}
Portugal	1.978×10^{-5}	2.641×10^{-5}	6.657×10^{-4}	1.256×10^{-5}	2.440×10^{-4}
Romania	2.804×10^{-5}	4.684×10^{-5}	1.979×10^{-4}	6.392×10^{-6}	1.444×10^{-4}
Serbia	5.421×10^{-5}	2.640×10^{-5}	3.692×10^{-4}	2.448×10^{-6}	4.418×10^{-4}
Slovakia	1.007×10^{-5}	2.132×10^{-5}	2.476×10^{-4}	1.028×10^{-5}	4.980×10^{-5}
Slovenia	1.152×10^{-5}	1.455×10^{-5}	8.033×10^{-5}	8.906×10^{-5}	1.258×10^{-4}
Spain	1.768×10^{-5}	2.057×10^{-5}	3.071×10^{-4}	8.636×10^{-6}	2.660×10^{-4}
Sweden	1.421×10^{-4}	5.595×10^{-5}	1.637×10^{-4}	6.932×10^{-5}	5.283×10^{-4}
Turkey	1.044×10^{-4}	5.973×10^{-4}	6.290×10^{-4}	9.970×10^{-5}	3.268×10^{-4}
UK	1.633×10^{-5}	1.2850×10^{-4}	1.963×10^{-4}	7.526×10^{-5}	1.159×10^{-4}

Table 5.A.1: MSE for all countries and categories over the period 2012 – 2019.

5.A.3 AGT and FPW interactions

Owing to the competitive roles between any pair of categories (see Table 3), except for when amensalism or commensalism may occur, the AGT and FPW interactions between all worry categories $P_{i,j}$ and a fixed category $P_{h,j}$, for all $i \neq h$, only depend on sign of the interaction coefficient $g_{h,j}$.

In fact, excluding the commensalism and amensalism interactions, we have

a) AGT interaction from a fixed category $P_{i,j}$ to any other category $P_{h,j}$ when

$$\begin{cases} g_{i,j} < 0, \\ g_{h,j} < 0, \end{cases} \cup \begin{cases} g_{i,j} > 0, \\ g_{h,j} < 0, \end{cases} \Longleftrightarrow \begin{cases} g_{i,j} \neq 0, \\ g_{h,j} < 0, \end{cases} \qquad \forall h \neq i \tag{5.7}$$

b) FPW interaction from a fixed category $P_{i,j}$ to any other category $P_{h,j}$ when

$$\begin{cases} g_{i,j} < 0, \\ g_{h,j} > 0, \end{cases} \cup \begin{cases} g_{i,j} > 0, \\ g_{h,j} > 0, \end{cases} \Longleftrightarrow \begin{cases} g_{i,j} \neq 0, \\ g_{h,j} > 0, \end{cases} \qquad \forall h \neq i. \tag{5.8}$$

5.A.4 Statistical tests on the AGT and FPW interactions

We use the paired t-test to assess whether *(i)* the averages of the relative frequency distributions of AGT and FPW among the concerns differ; *(ii)* the averages of the relative frequency distributions of AGT between any pairs of concerns, e.g., Environment vs Economy and Environment vs Safety, differ.

paired t-test	AGT vs FPW	
	statistic	p-value
Environment vs Economy	3.4392	0.0017
Economy vs Environment	-3.3977	0.0019
Environment vs Immigration	-2.3917	0.0232
Environment vs Safety	0.7844	0.4389
Environment vs Social issues	-2.4904	0.0185

Table 5.A.2: Paired t-test conclusions. The null hypothesis $H_0 : \mu_1 - \mu_2 = 0$ that the mean of the paired differences is zero versus $H_a : \mu_1 - \mu_2 \neq 0$ is rejected at the 5% level in all cases except for Environment vs Safety

paired t-test	AGT	
	statistic	p-value
(Environment vs Economy) VS (Environment vs Safety)	3.2088	0.0032
(Environment vs Economy) VS (Environment VS Immigration)	5.8655	$2.0316 \cdot 10^{-6}$
(Environment vs Economy) VS (Environment vs Social issues)	7.1664	$5.66191 \cdot 10^{-8}$

Table 5.A.3: Paired t-test conclusions. The null hypothesis $H_0 : \mu_1 - \mu_2 = 0$ that the mean of the paired differences is zero versus $H_a : \mu_1 - \mu_2 \neq 0$ is rejected at the 5% level in all cases

paired t-test	AGT		FPW	
	statistic	p-value	statistic	p-value
(Others vs Economy) VS (Others vs Environment)	6.4521	$3.97 \cdot 10^{-7}$	-6.4521	$3.97 \cdot 10^{-7}$

Table 5.A.4: Paired t-test conclusions. The null hypothesis $H_0 : \mu_1 - \mu_2 = 0$ that the mean of the paired differences is zero versus $H_a : \mu_1 - \mu_2 \neq 0$ is rejected at the 5% level in all cases

Supplementary Figure 1 provides a statistical description of the frequency distributions of AGT and FPW between the concerns by means of the box-and-whisker plots.

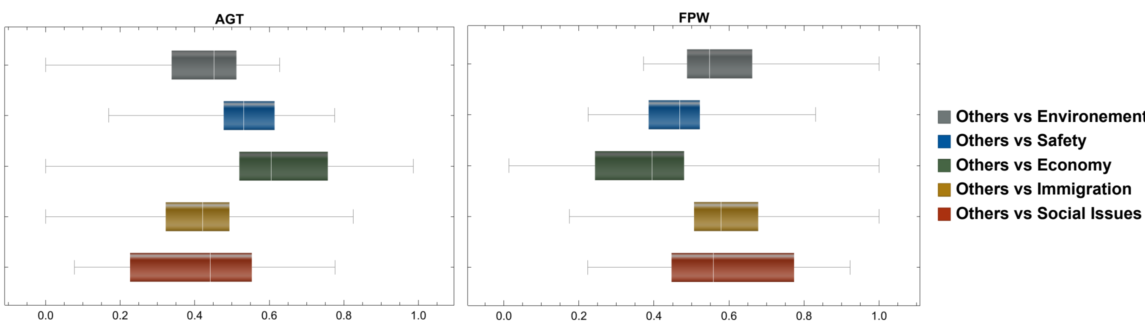

Figure 5.A.1: Box-and-whisker summary of the frequency distributions of AGT and FPW between the concerns for all worry categories and the Environment, Safety, Economy, Immigration, and Social Issues over all countries, respectively

Chapter 6

Towards a Testable Model of Reference Dependent Preferences with Biased Bayesian Updating

6.1 Introduction

In this thesis I presented four papers showing the impact of behavioural interventions in the environmental and health domains and a paper investigating how concerns for the environment interact with other sources of concern. The results of the papers included in this thesis can be rationalised by a model that I will introduce in this chapter.

My model of reference-dependent preferences builds on the work of Kahnemann and Tversky (1979) (from now K&T) and Kőszegi and Rabin (2006) (from now K&R). I build on their work to encompass the results of the previous chapters as well as well-replicated behavioural biases: the endowment effect, loss aversion and people's inherent preference for certainty.

The endowment effect was first introduced by Thaler (1980) and extended evidence was presented by Kahneman et al. (1991). The endowment effect refers to the fact that typically people demand a higher price to sell a product they own than they would be prepared to pay for it as a buyer. Evidence for this effect mostly comes from experiments where half of the participants are endowed with one good, and half the participants with a different one. Participants are then allowed to trade at prices they establish. Assuming that preferences are randomly distributed across the treatment groups, about 50% of participants would be expected to trade. Instead, the proportion of trades is often significantly lower, and the willingness to accept (WTA) stated by potential sellers is much higher than the willingness to pay (WTP) for the object stated by potential buyers. Kahneman et al. (1991) present evidence for this phenomenon using different procedures to elicit the WTA and WTP and several goods offered to potential traders. Replications are consistent with their findings and show that the WTA is typically an order of magnitude above the WTP. The main critique to this finding comes from Plott and Zeiler (2005), who propose that the WTA-WTP gap might be due to participants' misconceptions of the trading environment. To test this, they train participants before allowing them to trade, and find that the WTA-WTP gap disappears. However, a plausible explanation of why the effect disappears in their study, but remains a consistent experimental anomaly, comes from List (2003), Tversky and Kahneman (1991) and Novemsky and Kahneman (2005). These papers show that the endowment effect is likely to hold for inexperienced traders (people who did not expect to trade an object) but the effect is less pronounced for experienced ones (buyers and sellers who expected to trade an object on the market). As many experiments test the effectiveness of an intervention on participants without prior experience, being able to capture this bias seems to be a desirable feature of any model attempting to capture the impact of a behavioural intervention.

Experimental evidence also suggests that the majority of people display behaviours that are inconsistent with strict risk aversion or risk lovingness, but can be explained by loss aversion. Kahnemann and Tversky (1979) show strong evidence of this via a series of experiments. They propose that these behaviours can be explained by choices made through a value function. In their framework, a choice process consists of an "editing" and an "evaluation" phase. In the editing phase the individual considers the offered prospects and may simplify them according to some heuristics. Following this phase, participants evaluate the prospects available to them and choose the one with the highest value, weighting possible losses more than possible gains. Agents who display loss aversion, in turn, display a preference for the status quo, as the status quo guarantees the outcome, while any risky change may cause a loss with respect to a reference point. As the results presented in Chapter 4 hinge on the status quo bias, I build my model following the tradition of previous behavioural papers, allowing agents to be loss averse. Kahneman and Tversky also propose that participants choose prospects according to a decision weight $\pi(p)$, where $\pi(\cdot)$ is a function weighting the objective probabilities of outcomes occurring. More recent literature, e.g., Gonzalez and Wu (1999), attempts to estimate the extent to which participants weigh probabilities, but while there might be disagreements over the function to use, the findings of Kahnemann and Tversky (1979) are largely uncontested. In my model, I account for choices made according to decision weights and put more structure on the updating of probabilities used by the agent to evaluate prospective choices.

Probability weighting also helps explaining a third main finding of the behavioural literature: people display a strong preference for certainty over risk, even when choosing the certain payment over a lottery violates expected utility theory. Kahnemann and Tversky (1979) show that people assign a higher probability to outcomes considered certain, relative to those that are only probable. Already Allais (1953) had offered evidence of the certainty effect, as he showed that people consistently make choices over monetary outcomes that are inconsistent with expected utility theory, regardless of the risk attitudes of the participant. Kahneman et al. (1991) show that the effect holds even over non-monetary outcomes. These violations, formally violations of the substitution axiom, are inconsistent with participants making decisions according to objective probabilities, but can be easily explained by considering decision weights that over-weigh certain outcomes. By assigning a higher weight to low-probability events and a lower weight to high-probability events, participants perceive a low certain amount to be preferable to a lottery with higher expected utility. As my model encompasses findings of experiments ran during the pandemic, when prospective outcomes were uncertain, this is a desirable feature to include.

I build my model to encompass these effects but depart from K&T and K&R's models in four ways. First, I consider preferences over consumption and stated preferences, i.e., opinions (preferences) participants express over alternative policies, that directly contribute to their utility. Models of reference-dependent preferences have been used to study individual decisions and risk attitudes, but the literature often considers utility to depend only on material consumption. K&T mention that their model could be applied to "any class of consequence", but their analysis focuses on monetary outcomes for convenience. In considering stated preferences, I extend the reach of the model, and make it suitable to frame experiments and surveys. Second, most models of reference dependent preferences are static, e.g., Kahnemann and Tversky (1979) and Kőszegi and Rabin (2006) or fully dynamic. For instance, Kőszegi and Rabin (2009) build a dynamic model of reference dependent preferences to study under-saving and Bénabou and Tirole (2011) build a model where choices and payoffs at later times depend on the memory an agent has over previous actions. Instead, I consider a two-period model and a signal (e.g., a behavioural treatment) that agents receive between two periods. Agents make choices that are independent across the times, except for the probabilities they attach to events, which will be influenced by the signal. This allows me to consider the change in choices induced by an intervention through agents' heterogeneous priors and updating without needing to build a fully dynamic model or one where choices are serially correlated or bounded by previous actions. Third, the signal, e.g., an experimental treatment, causes an update in preferences or reference points, which may be stochastic. I consider the reference point of an agent to be dependent on the identity they aspire to. The identity can be consistent across multiple dimensions, e.g., an agent wishing to be a good environmentalist considers regularly recycling and reducing their carbon footprint as much as possible to be part of their reference point, but could also differ across dimensions, e.g., an agent may wish to recycle but also to travel to a tropical island at least once a year, even though the latter action increases their carbon footprint. This definition of identity is in line with Bénabou and Tirole (2011), but in my model agents need not infer their identity in the second period from past choices and could change their identity entirely following a signal. Finally, instead of relying on Bayesian updating, I allow agents to update in a biased fashion. Specifically, agents will discount information coming from signals that do not align with their identity, update in a Bayesian way following signals perceived as neutral and over-update following signals perceived to be in line with their identity. This form of biased updating, combined with heterogeneous priors, can explain the heterogeneity in the impact of a treatment at individual level. This framework can also account for interventions that foster polarisation and interventions that reduce it, i.e., treatments that increase or decrease the difference in averages between two groups. For instance, consider three agents Anna, Bob and Charles, who have different priors over the importance of tackling climate change: Anna is neutral to climate change, Bob is a climate denier and Charles is an environmentalist. Anna believes scientific findings and takes them at face value, Bob believes that that scientists always exaggerate the seriousness of an issue, and Charles believes that scientists always understate environmental issues. Suppose that the three agents participate in an experiment where the treatment is a video of a scientist describing climate change as an urgent issue and urging people to support a carbon tax. This signal will cause updating for all agents. Anna now perceives a higher urgency of dealing with climate change and her posterior is the Bayesian update of her prior. Bob will now perceive the urgency as lower (scientists cannot be trusted!) and Charles will perceive a higher need of action. Imagine asking all three agents their support for a carbon tax pre- and post- signal: Anna will state a higher support post treatment. Bob will either not change his support, by stating the lowest in both cases, or he will state a lower support after the information received. Charles will state either the same support (the maximum) or a higher one. With this form of updating treatments can induce convergence, e.g., if the signal is perceived positively by a group and neutrally by another (see Anna and Charles), or polarisation, e.g., if the signal is perceived negatively by some and positively by others (see Bob and Charles above). In this vein I define an “effective” treatment as one that induces an average treatment effect in the direction intended by the experimenter or policymaker. A treatment is instead “ineffective” if the average treatment effect is not significantly different from zero. Finally, a treatment triggers “reactance” if the average treatment effect is in the opposite direction from the one intended by the experimenter. This classification is highly practical, as it is based on the possible outcomes of the statistical hypothesis testing the average effect of a treatment, but it does not rule out convergence or polarisation. For instance, consider the same video of the scientist introduced above. Testing whether the treatment is on average successful entails comparing the level of support for the tax between the treatment and control group. The treatment is effective if the average level of support for a carbon tax in the treatment group is higher than in the control group, i.e., the difference in the level of support for the tax between the treatment and control is positive and statistically significant. The same treatment is considered to be ineffective if the difference between the level of support for the tax in the treatment and control group is not significantly different from zero. Finally, the intervention triggers reactance if the difference in the level of support for the tax between the treatment and the control group is negative and statistically significant. The percentage of people like Anna, Bob and Charles determines the overall effectiveness of the treatment, but within a subgroup the treatment effect needs not be the average. In this model, the direction of the individual effect, and hence the driver of polarisation or convergence, depends on whether the intervention is perceived to be in line or against the participant's identity. It is plausible then to have a treatment that on average raises the support for the tax, but increases polarisation between the Bob and Charles in the sample. Conversely, the treatment could promote convergence between the Anna and Charles in the sample, but be on average ineffective.

In Section 2 I discuss the theoretical underpinning of the model, discuss updating and define a preferred personal equilibrium. In Section 3 I discuss how the model helps conceptualising each of the papers presented in this thesis. Finally, in Section 4 I conclude by discussing the limitations of this model and avenues for future research.

6.2 The model

To think about the impact of a (behavioural) intervention I consider a two-period model of reference-dependent preferences with times $t \in \{t_0, t_1\}$, in which a decision-maker maximises subjective expected utility at each period. The utility function captures the utility the agent derives from material consumption and from stated preferences. The timing of the model is as follows: at time t_0 the agent maximises subjective expected utility given some priors (decision weights) over the distribution of outcomes and reference points; between t_0 and t_1 the agent receives a signal; at time t_1 the agent again maximises subjective expected utility with the updated probabilities, preferences and reference points. I assume that in each period an agent first learns the reference points (or forms beliefs over their distribution) and then makes consumption decisions. Importantly, there is no action taken in t_0 which binds decisions in t_1, so decisions across the two time periods can change, e.g., the agent is not signing contracts at t_0 or somehow restricting the choice set at t_1. However, the two periods are not independent, as the probabilities assigned to events occurring at t_1 are updated beliefs from the priors the agent held at t_0.

6.2.1 Reference-dependent utility

A person's utility for a riskless outcome at each time period t is defined to be $u_t(c_t \mid r_t)$ where c_t is a vector $c_t = (c_{1t}, c_{2t}, ..., c_{kt}) \in \mathbb{R}^k$ of consumption or stated preferences at time t and $r_t = (r_{1t}, r_{2t}, ..., r_{kt}) \in \mathbb{R}^k$ is a vector of reference levels of consumption or stated preferences at time t.[1] The reference point r_t depends on the agent's information set at time t and their identity I_t. The utility function of an agent at a given time will be composed of two elements: $u_t(c_t \mid r_t) \equiv m_t(c_t) + n(c_t \mid r_t)$, where $m_t(\cdot)$ is the consumption utility obtained by an expected utility maximiser choosing consumption according to decision weights, and $n(c_t \mid r_t)$ is a gain-loss utility that depends on the level of consumption and its distance from a reference point. This formulation allows for an absolute utility from consumption and a gain-loss function showing the extra utility derived by the agent for choosing a consumption level with respect to a reference one. For instance, a person attending a Michelin star dinner will derive an absolute level of utility from the dinner (e.g., the reduction in hunger and how much they like the food) and an extra utility term (positive or negative) that depends on the reference point. For a Michelin-star reviewer this is likely to be zero, but for someone who was brought to the restaurant as a surprise the experience it is likely to create a gain. The gain-loss function respects the properties of the value function introduced by K&T. For simplicity, and following Köszegi and Rabin (2004), I consider utility to be additive and separable across dimensions, so $m_t(c_t) \equiv \sum_{k_t}^{K_t} m_{kt}(c_{kt}) \forall t$ with $m_t(\cdot)$ twice differentiable and strictly increasing. The same is true for the reference utility vector $n(c_t \mid r_t) \equiv \sum_{k_t}^{K_t} n_k(c_{kt} \mid r_{kt}) \forall t$. Notice that the specification assumes separability across goods, so the model will not capture beliefs and consumption decisions that are complementary. For instance, the model allows me to capture the utility of supporting a carbon tax and the utility of eating less meat, but if the agent derives any extra utility in consuming less meat when they also support a carbon tax I will not be able to capture

[1] Henceforth the term consumption will be intended loosely to mean anything that the agent derives utility from, so c_k might capture the agent's stated preference for a policy, e.g., their level of support for a tax/subsidy, an intended behaviour, e.g., stated compliance with social distancing, or a realised consumption, e.g., the number of car trips the agent makes. The distinction between consumption and preferences for policies will be clarified when considering the difference between the consumption level chosen and the reference point.

this interaction term. This approach is similar to one that considers decisions agents make under narrow framing: each consumption decision is taken without accounting for the impacts of that decisions on others. In the way the model is specified, a period can be seen as the duration in which an agent makes a choice and the outcomes of that choice are realised, e.g., the choice to participate in a lottery is made and the lottery outcome are realised before the beginning of the next period.

6.2.2 Stochastic outcomes and reference points

Consumption levels and reference points may also be stochastic. At time t if the agent believes c_t to be drawn according to the probability measure F, the person's utility is:

$$U_t(F \mid r_t) = \int u_t(c_t \mid r_t) dF(c_t) \tag{6.1}$$

The reference point can similarly be made stochastic. If the agent perceives the reference point to be the probability measure G over $\mathbb{R}^k$ and consumption to be drawn according to F the person's utility at time t becomes:

$$U_t(F \mid G) = \int \int u_t(c_t \mid r_t) dG(r_t) dF(c_t) \tag{6.2}$$

Considering stochastic outcomes is especially important in settings with scientific uncertainty. For instance, consider an agent at the beginning of the Covid-19 pandemic choosing which precautionary behaviours to undertake. The agent knows that with some probability they might catch the virus, and if they do with some probability the symptoms might be serious. These probabilities affect how desirable preventive behaviours are. However, the exact probabilities of these events occurring are unknown, so decisions will be made based on the perceived likelihood of these events. Similarly, consider a person whose target identity is to be "social": should their reference point during the pandemic be not to see friends at all? To reduce the number of meetings? Or the number of people met? If there is no clear answer the agent will consider the lottery where each of these outcomes can be the reference point. With stochastic outcomes, the person will consider a gain or loss from a reference point by considering all possible consumption outcomes and comparing them to all possible reference lotteries at a given point in time. For instance, in our Covid-19 example, an agent who is unsure about their reference point will form some beliefs over whether they should expect to never go out or go out with some frequency. When making the decisions to see friends, they need to balance the possible realisations of the reference points, knowing that the meeting yields the possibility for both a utility gain and a utility loss depending on the realised reference point. For instance, going out twice when the reference point is to never go out entails a loss, while going out twice when the reference point is to go out at least once entails a gain. More generally, the expected utility from any lottery is then a weighted average of the times in which the outcome is perceived as a gain and those in which it is perceived as a loss relative to possible draws of the reference point. Neither F nor G need to correspond to the objective probability distributions over an event. For instance, an agent might believe that a fair coin is more likely to land heads than tails and form F and G accordingly. Agents will maximise utility given decision weights held over consumption levels and reference points.

6.2.3 Properties and implications of the gain-loss function

Given separability of the gain-loss function, the change in overall utility due to the consumption level in a domain can be expressed as $n_k(c_{kt} \mid r_{kt}) \equiv \mu(m_{kt}(c_{kt}) - m_{kt}(r_{kt}))$. The model is further simplified by assuming that the gain-loss function is not time-dependent, and instead depends only on the gain (loss) in consumption due to choices above (below) the reference point for a specific consumption item. In line with K&T I assume that $\mu(\cdot)$ satisfies five conditions. Specifically:

A1: $\mu(x)$ is continuous and twice differentiable for $x \neq 0$ and $\mu(0) = 0$.

A2: $\mu(x)$ is strictly increasing.

A3: loss aversion is satisfied, so for any $y > x > 0$ we have $\mu(y) + \mu(-y) < \mu(x) + \mu(-x) < 0$.

A4: the function exhibits diminishing sensitivity, so $\mu''(x) \leq 0$ for $x > 0$ and $\mu''(x) \geq 0$ for $x < 0$. [2]

A5: the function is steeper in losses than in gains, making the agent very risk averse around the reference point: $\mu'_-(0)/\mu'_+(0) \equiv \lambda > 1$ where $\mu'_+(0) \equiv lim_{x\to 0}\mu'(|x|)$ and $\mu'_-(0) \equiv lim_{x\to 0}\mu'(-|x|)$

The agent receives no utility for being exactly at the reference point, positive utility when above the reference point and negative utility when below the reference point. The gain-loss utility of the agent is increasing in the positive distance from the reference point, and the gain (loss) is proportional to the distance from the reference point for that good. Losses loom larger than gains, e.g., losing \$10 hurts the agent more than winning \$10 increases their utility. Losing (winning) \$100 hurts (benefits) the agent more than losing (winning) \$10. The utility gain or loss felt in one domain is independent from the rest of the consumption level chosen. The intuition holds for monetary and non-monetary outcomes. Fixing the

[2] As Kőszegi and Rabin (2006) note relaxing A4 to have $\mu''(x) = 0$ when $x \neq 0$ (linear preferences) does not alter the model significantly and allows to expose the ideas in a simpler manner.

outcomes at a given point in time, a lower reference point increases utility and, absent a shock, preferences exhibit a status quo bias, as the status quo allows to avoid incurring losses. For the function to capture stated preferences or intended behaviours a caveat needs to be added: the agent could state a preference below a reference point and bear the loss associated to it, but there is no plausible way of being above the reference point so $m_{kt}(c_{kt}) - m_{kt}(r_{kt})$ has an upper bound at zero, when $c_{kt} = r_{kt}$. For instance, a climate denier would consider having no carbon tax as a reference point- why have it when climate change is not real? Imagine asking them whether they support a carbon tax. Stating zero meets the agent's reference point, so there is no gain-loss utility, and allows the agent to derive utility from their statement through $m_t(\cdot)$. However, no statement can bring the agent above their reference point. If the climate denier stated a positive level of support for a carbon tax ($c \neq r$), they would incur a utility loss by being below the reference point. More generally, if there is a preferred level of support any statement that differs from the real level induces a loss, regardless of whether the support stated is above or below the preferred one. This implies that the gain-loss utility is bounded at zero for beliefs. If the reference point and consumption level are stochastic it is also plausible for an agent to lose by stating too high or too low a support level than the realised reference point, but it is still impossible to gain from a statement. This has important consequences in an experiment, as it takes away incentives to state anything different that the agent's true (perceived) preferences for a policy.

Proposition 1. *If μ satisfies A1-A5 (bounded for stated preferences) the following will hold:*

1. *For all F, G and G' such that the marginals of G' first-order stochastically dominate the marginals of G in each dimension, $U(F \mid G) \geq U(F \mid G')$.*
2. *Fixing a time, for any $c, c' \in \mathbb{R}^K$ with $c \neq c'$, if $u(c \mid c') \geq u(c' \mid c') \rightarrow u(c \mid c) > u(c' \mid c)$*
3. *If $\mu''(x) = 0 \ \forall x \neq 0$, for any F, F' that do not generate the same distribution of outcomes in all dimensions, if $U(F \mid F') \geq U(F' \mid F') \implies U(F \mid F) > U(F' \mid F)$.*

This implies that a behavioural intervention changing the perceived probability distributions of reference points G or the vector of reference points to one that first-order stochastically dominates the previous one induces the agent to perceive a higher utility. If F is also allowed to change between the two periods so that $F_{t_0} \neq F_{t_1}$ and $G_{t_0} \neq G_{t_1}$ the optimal choices in t_1 will differ from those in t_0 and the agent can (but needs not) be better off after the signal. However, this increase in utility is lost once the agent becomes accustomed to the new reference point or lottery. Parts 2 and 3 imply that if an agent was consuming at their reference point and is willing to change consumption, the new consumption is strictly preferred if that consumption becomes the new reference point. Consider an intervention that makes a person who ate one vegan meal a week (c') to reduce their carbon footprint (a motivation that is part of their identity I) start eating two vegan meals a week (c). If the person complies, it must be because they expect a higher utility from doing so than from their current behaviours. The same person will continue to eat two vegan meals a week if this becomes their reference point, as not doing so would now be considered a loss. However, in setting the new reference point the agent is less likely to experience a gain in utility from being above this level, i.e., it now takes at least three vegan meals a week to be above the reference point. Assuming $\mu''(x) = 0 \ \forall x \neq 0$ allows this statement to hold even when the agent is making a choice under risk. K&R show that if $m(\cdot)$ is linear and $\mu(\cdot)$ satisfies the assumption above, then there exists a $\{v_k\}_{k=1}^{K}$ such that $u(c|r) - u(r|r) = \sum_{k=1}^{K} v_k(c_k - r_k)$ (see the proof for proposition 2 in K&R).

6.2.4 Endogeneity of the reference point

The literature provides some evidence that expectations help determining the reference point, e.g., Mellers et al. (1999), Breiter et al. (2001) and Medvec et al. (1995). However, defining the reference point as expectations the person held in the recent past does not bring us closer to how people form the expectations to begin with. The treatment of the reference point in this chapter is closer to Bénabou and Tirole (2011): the initial reference point (prior) is determined by the identity of a person, i.e., the prior depends on what the agent aspires to be. The identity of a person is a vector $r \in \mathbb{R}^K$ with each entry corresponding to the reference level of consumption an agent wishes to reach. In defining reference lotteries in this fashion, I do not follow K&R in assuming that agents hold rational expectations and correct beliefs. Instead, I allow agents to hold decision weights as their priors and update in a biased way. In a model without behavioural interventions and correct priors, the person's reference points are their probabilistic beliefs about consumption held before the consumption decision is made and beliefs are correct like in K&R, but may differ across identities. That is, with a neutral signal, this agent updates in a Bayesian way and infers the correct posteriors from their possibly biased priors. Additionally, I allow the signal the agent receives between t_0 and t_1 to affect future choices through two channels. First, the signal causes updating from the decision weights held as priors (for those who do not consider an event to be certain). Second, updating differs according to whether the agent perceives the signal to be in line, neutral or against their identity. These channels can induce changes in the optimal consumption levels and reference points held in the second period and hence promote behavioural changes.

6.2.5 Behavioural interventions, probability weighting and updating

In neoclassical models, agents are assumed to be rational expected utility maximisers: for any lottery $l = (x_1, p_1; ..., x_m, p_m)$, where p_i denote the probability of the outcome x_i and $\sum_{i=1}^{m} p_i = 1$ the agent perceives $U_i = \sum_i p_i u(x_i)$ and maximises utility accordingly. In this model, I assume agents to be maximising expected utility subject to subjective probabilities (decision weights) $\pi_{it}(p_t)$. While the sum of these weighted probabilities needs not add up to 1, it is convenient to assume that they do to avoid having to redefine the probability measure F and G. Hence the identity of a person simply scales the objective probabilities in favour of the beliefs of the ideal self.

A signal s, such as information provision, induces updating where the posterior belief over an event θ is $\pi_{it}(\theta|s) = P(\theta|s)f(I,s)$ where $P(\theta|s)$ is the Bayesian posterior probability computed based on the agent's decision weights and $f(I,s)$ shifts the probability according to whether the signal is perceived to be in line with the agent's identity. $f(s,I) = 1$ for signals perceived as neutral, $f(s,I) < 1$ for signals perceived against the agent's identity and $f(s,I) > 1$ for signals perceived to be in line with the agent's identity. If the signal is not understood $f(s,I) < 1$ regardless of whether the signal is in line with the person's identity, but for a given level of understanding $f(s,I)$ is lower for agents that perceive the signal as not in line with their identity. This is capturing the fact that agents update based on their understanding of a signal, and that the posterior probabilities are not correctly perceived when the information provided is hard for participants to understand. Regardless of whether the signal is in line with the person's identity or not, if the agent assigns probability 1 or 0 to a consumption level and reference point, there will be no updating. Structuring the updating in this fashion makes the perceived probability distributions F_{t_1} and G_{t_1} depend on the prior, the signal received and the person's identity. The distributions F_{t_1}, G_{t_1} may be narrower or wider than the initial F_{t_0}, G_{t_0} and have different moments of the distribution.

A signal can then make agents change behaviours through changes in: i) the agent's preferences, making $m_{t_1}(c \mid s) \neq m_{t_0}(c)$; ii) the agent's reference point, making $r_{t_1|s} \neq r_{t_0}$, iii) the probabilities attached to different outcomes, F and G, if c_t and r_t are stochastic. If the behavioural intervention causes either i), ii) or iii), the optimal consumption bundle chosen at t_1 can differ from the optimal consumption bundle chosen at t_0.

Notice that assuming additive separability allows a signal targeted at one dimension to indirectly affect the consumption level chosen overall. This model allows me to capture how the demand for goods other than the one affected by the signal changes through the budget constraint, as changes in either $m(x)$ (with x being the target of the signal) or $r_t(x)$ or both make the agent choose a different optimal consumption level, which allows the agent to adjust consumption of goods other than x. This is also true for behaviours. For instance, consider an intervention aimed at making the agent comply with social distancing. While the model does not allow to capture the correlation between compliance with social distancing and video calls with friends, a person optimally changing their social distancing behaviours can have a different amount of video calls given the extra time available to do so. Hence, in the second period an agent who becomes more (less) compliant with social distancing could optimally increase (decrease) the number of video calls with friends. Changes to the optimal demand for other goods can happen either through a spillover effect, i.e., the signal causes changes in preferences or reference points in two or more dimensions, or through a rebound effect, e.g., changes in time the agent can allocate to different activities. In the video call examples, the agent could increase the time spent on video calls because they are perceived as more valuable (a change in preferences) or due to the extra time spent at home (a rebound effect). In the next sections I focus mostly on signals that affect the perceived probabilities, as a one-time intervention is unlikely to drastically change an agent's preferences or identity.

6.2.6 Preferred Personal Equilibria

Allowing agents to hold possibly biased beliefs about F and G and update accordingly means not requiring them to correctly identify the environment they face in equilibrium like in K&R (2006). Specifically, a preferred personal equilibrium will only require agents to correctly maximise their subjective expected utility given a reference point vector and the updating that took place between the two periods. Formally, assume that the agent has probabilistic beliefs described by the distribution Q over $\mathbb{R}$, capturing the perceived distribution over possible choice sets $\{D_l\}_{l\in\mathbb{R}}$ they might face, where each $D_l \in \Delta(\mathbb{R}^K)$.

DEFINITION 1: A selection $\{F_l \in D_l\}_{l\in\mathbb{R}}$ at any period is a preferred personal equilibrium (PPE) if for all $l \in \mathbb{R}$ and $F_l' \in D_l$, $U(F_l \mid \int F_l dQ(l)) \geq U(F_l' \mid \int F_l dQ(l))$ and $U(\int F_l dQ(l) \mid \int F_l dQ(l)) \geq U(\int F_l' dQ(l) \mid F_l' dQ(l)$ for all $\{F_l' \in D_l\}_{l\in\mathbb{R}}$

This is stating that at each time the agent is maximising utility given the perceived probabilities they assign to realisations of outcomes and reference points. The agent can mispredict the environment they face (through decision weights and updating) but conditional on those probabilities they are choosing the consumption plan that maximises utility in each period. If they expect to choose F_l from the choice set D_l, then given the expectations over possible choice sets, they expect the distribution of outcomes $\int F_l dQ(l)$. With these expectations as the reference point, the agent should be willing to choose F_l from D_l and would prefer it to any other $F_l' \neq F_l$ available. Consider a person deciding whether they want to recycle. The choice set at the time in which the agent is throwing away an object is the decision of whether to recycle or not at the cost of recycling, e.g., walking to the nearest recycling bin. The person's reference point is the probabilistic distribution over utility outlays and recycling behaviour determined by the planned behaviour in each choice set. That is, the plan to recycle depends on each possible cost of recycling combined with the distribution over possible choice sets- i.e., the agent's beliefs about the costs they might face. For instance, the decision to recycle might depend on the distance from the nearest recycling bin or weather outside, affecting how costly walking to the nearest bin is. In a PPE, the planned behaviour is optimal given the reference point and has the highest ex ante expected utility. If the agent expected to recycle only when possible with a short walk it must be that i) whenever the walk is short the agent will in fact recycle and ii) that choosing to recycle only with short distances was optimal *a priori*, e.g., choosing to recycle no matter the distance would yield lower expected utility. Theorem 1 in Kőszegi (2005) establishes that if $\int D_d Q(l)$ is convex, compact and a closed set and $U(F \mid F)$ is continuous in F a PPE exists. The result holds in my model, as considering beliefs only bounds the gain-loss utility at zero and the stated preferences to the scale in which the experimenter asks questions. For a single period, deterministic choice set and reference points and correct beliefs around them, the agent will act in a way that is consistent with a model based on consumption utility, without reference dependence:

Proposition 2. *Consider a time period where Q is a lottery putting probability 1 on a choice set consisting of all convex combinations of a set $D*$ of deterministic outcomes. If $\mu''(x) = 0$ for $x \neq 0$ a lottery is a PPE if and only if it puts probability 1 on an outcome that is a solution to $argmax_{c' \in D*} m(c')$*

A consumption level c that maximizes the consumption utility is a PPE. Consuming c allows the agent to have zero gain-loss utility and maximize consumption utility. Intuitively, choosing a different bundle would either not maximize consumption utility or create a sense of loss by not choosing the reference level of consumption. So from an ex ante perspective the highest expected utility can be obtained by choosing exactly the deterministic outcome that maximizes consumption utility.

6.2.7 What can the model explain?

Structuring reference-dependent preferences in the way described above allows to explain the heterogeneity in the impact of behavioural interventions and capture interventions that reduce polarisation as well as interventions that increase it. My contribution is two-fold. On the one hand, previous studies find that some behavioural interventions are effective at changing stated preferences and behaviours, while others are ineffective and some even trigger reactance. A focus on the average treatment effect does not allow to pinpoint what is causing the reaction to the signal. I offer three possible mechanisms for why people react to the signal they receive: changes in preferences, reference points and updating of probabilities. Second, it offers an explanation for heterogeneous treatment effects. Depending on the priors and identities of the participants, their actions in the second period can be more or less in line with the signal. Interventions could increases polarisation, either because all participants update in the same direction but some update with greater intensity than others, or because different subgroups update in different directions. However, treatments could also favour convergence when either all groups update in the same direction and get closer in the process, or sub-groups update in different directions, moving closer to each other.

6.3 Applications

In this section I use the model I introduced above to frame the papers presented in this thesis. Hence, an agent's utility function can be expressed as $U_t(c_t, r_t)$ and the perceived probability measures as $F_t(I_t, s)$ and $G_t(I_t, s)$, where I_t denotes the identity of the participant at time t and s captures the signal received between the two periods. In Chapters 1-4 of this thesis I discussed participants' reaction to an experimental treatment, where by design the data provided to participants was equal across participants. However, different papers tested different mechanisms. In Chapter 1 I showed how identity can be leveraged to reduce the consumption of carrier bags. Chapters 2 and 3 study how framing the same information differently affects understanding of the information presented and policy preferences through different updating. Specifically, in Chapter 2 participants in the treatment and control group saw the same data on different colour scales, while in Chapter 3 participants in the two groups saw data displayed on different scales (linear or logarithmic). Chapter 4 extended the work to study the impact of two nudges used in isolation or together, providing different amounts of information to the control and treatment groups. In all the chapters individual treatment effects are expected to vary (in sign and dimension) based on the individual level of understanding, the identity of a participant, and priors about the scenario presented. However, focusing on the differences between the treatment and control groups allows me to attribute the average treatment effect to a single mechanism.

6.3.1 Lowering the consumption of single-use carrier bags

In Chapter 1, I presented the results from a field experiment ran in Naples, aimed at reducing the consumption of single-use carrier bags.

Previous attempts to reduce their consumption relied on imposing levies on their purchase. However, the effects of these levies have been short lived and overstated (Rivers et al., 2017). To reduce the environmental impact of consuming single-use bags, the EU imposed both a levy on single-use carrier bags and a ban on plastic bags. However, the levy was unsuccessful at drastically reducing consumption and non-plastic bags also pose a large threat to the environment. The production of biodegradable bags relies on materials derived from plastics, and the bags are not easy to recycle. Additionally, biodegradable and oxo-biodegradable bags that are not properly treated have very low deterioration rates, especially in soil and marine environments (Eerkes-Medrano et al., 2015; Napper and Thompson, 2019). Hence, reducing the demand for single-use bags is desirable even in the absence of plastic bags.

Previous studies tackling this issue focused on increasing the consumption of reusable grocery bags, assuming that this would lower the consumption of single-use bags (Martinho et al., 2017; Rivers et al., 2017). They broadly classified reusable bags as perfect substitutes for single-use bags. A possible utility function to capture this takes form $m(c) = ac_1 + bc_2 + c_3$, where c_1 denotes the consumption of single-use bags, c_2 the consumption of reusable bags, a and b are positive constants capturing the marginal utility of buying a single-use and reusable bag respectively (with $a, b \in R$) and c_3 captures a numeraire good, e.g., monetary wealth, with $c_3 \in R$.

Consider a supermarket shopper who buys one bag when shopping for grocery, so $c_1, c_2 \in \{0, 1\}$ and $c_2 = 0$ if $c_1 = 1$. This consumer will choose either the bundle $c^1 = (1, 0, y - p_1)$ or the bundle $c^2 = (0, 1, y - p_2)$ where y denotes the consumer's income, p_1 is the cost of a single-use carrier bags and p_2 the price of a reusable bag. To make their choice, the shopper will consider the perceived marginal utility derived from each bag and the prices they demand on the market. Whenever $\frac{a}{b} > \frac{p_1}{p_2}$ or $a > b\frac{p_1}{p_2}$ the consumer will prefer buying the single-use bag.

Before the introduction of the levy bags were given away ($p_1 = 0$). In this setting, unless the consumer perceived $a \leq 0$, the single-use bag would be preferred to the reusable bag.

The only preferred personal equilibrium for any consumer with $a > 0$ would be to opt for the single-use bag and the only preferred personal equilibrium for any consumer with $a \leq 0$ would be not to never consume single-use bags. Raising the price of single-use carrier bags through a levy $t > 0$ can make a consumer that preferred buying a single-use bag prefer buying a reusable bag, that is $b\frac{p_1}{p_2}(= 0) < a < b\frac{t}{p_2}$. The imposition of a levy here would fail only if the levy was not high enough. This means that a policymaker would always be able to change the preferred personal equilibrium of an agent by choosing t^* such that $a < b\frac{t^*}{p_2}$ and once the agent finds it optimal to consumer reusable bags they would never consume single-use bags again.

At a first glance, this might seem a reasonable approximation of the choice grocery shoppers face at the cashier. However, the data reveals that the initial drop in consumption of single-use carrier bags vanished some time after the introduction of the levy. Allowing preferences to be reference-dependent allows to explain this phenomenon. Assume that $\mu(\cdot)$ satisfies A4 and $\mu(x) = x$ for $x > 0$ and $\mu(x) = \lambda x$ for $x \leq 0$, with λ capturing the extent of loss aversion displayed by the consumer. If a consumer buys a bag, the disutility incurred is bounded between p_1, capturing the disutility if the consumer expected to spend p_1 or more to acquire it, and $(1 + \lambda)p_1$ if the consumer expected to get the bag for free.

Before the introduction of the levy, consumers perceived no loss from purchasing a single-use carrier bag ($p_1 = 0$). The loss perceived in purchasing a single-use carrier bag after the introduction of the levy is bounded between t and $(1 + \lambda)t$. Consumers now have two incentives to avoid single-use bags. First, the levy increases the price of purchasing a single-use bag, triggering a substitution effect as in traditional models of consumer theory. Second, if the consumer continues to assume that single-use bags will be given for free, having to pay a positive price for one will cause the consumer to be in the loss domain.

Assuming that a, b and λ differ across individuals the model can capture the existence of multiple preferred personal equilibria: *i)* if $a \leq 0$, agents optimally set their consumption of single-use bags to zero before and after the introduction of the levy; *ii)* if $0 < a < t$, agents optimally bought single-use bags before the levy and do not buy them now; *iii)* if $0 < t < a < (1 + \lambda)t$, consumers optimally bought single-use bags before the levy, respond to the levy by not purchasing single-use bags before they adapt their reference point, but if the reference point becomes paying the levy, they start purchasing single-use bags again; and *iv)* if $a > (1 + \lambda)t$ the unique PPE is to always purchase a single-use carrier bag. For the third group of consumers, the introduction of the levy initially lowers the consumption of single-use bags. However, once their reference point is adjusted to take into account the price they will need to pay for the bag, the utility received from purchasing a single-use bag is again higher than the price paid to obtain one, explaining the new rise in consumption.

K & T suggest that, on average, people value losses twice as much as gains, or $\lambda = 2$. Single-use bags typically cost 0.05 or 0.1. Even if the agent did not anticipate the levy, these costs imply that if the monetary benefit of purchasing a single-use bag was higher than 0.2 single-use bags would still be preferred. One could extend the model to consider consumers who attach a probability $q < 1$ to having to pay the levy. This would capture consumers who are at first unsure about when the levy will enter into force, or those who think that shops will still give bags away for free. However, the intuition would remain similar, and suggests that the levies create too low a personal cost to be effective.

The experiment presented in Chapter 1 relies on imposing a utility cost on consumers who purchase a bag at the cashier, and providing a utility gain for those who do not purchase one. In designing the intervention, we exploited the fact that people shopping in the area treated are likely to have homogeneous preferences on certain dimensions, i.e., a shared identity. In particular, we leveraged place attachment and football preferences to create utility costs and gains. The treatment worked as follows: for any customer buying a single-use carrier bag we donate the equivalent monetary amount to a charity founded by the Juventus captain Chiellini (an "anti-charity"), an institution that is likely to be perceived negatively by the customers of the supermarket. Vice versa, for any customer not purchasing a bag, we donated the same amount to a local charity working with children, an association that is likely to be perceived positively by the customers of the supermarket. Loss aversion suggests that the value of the utility loss incurred in having to buy the bag will be larger than the value of the utility gain obtained by bringing one from home. However, both implied donations can be modelled as increases in the cost of a single-use bag. The donation to the anti-charity constitutes a utility cost incurred in buying the bag, while the donation to the charity captures the (smaller) utility gain foregone by having to buy a bag. This changes the consumers optimal decision, making buying a single-use bag a preferred personal equilibrium only if $a > b\frac{t^{*}+d_J+d_N}{p_2}$, where d_J captures the loss given by the implied donation to the Juventus charity, d_N the foregone gain in not being able to donate to the Naples charity and $d_J > d_N \geq 0$ due to loss aversion.

We gathered data on the sales of single-use bags before the introduction of the treatment, during the treatment period and for two weeks after the treatment ended. We observed a sharp decrease in the consumption of single-use carrier bags from the second week of the treatment, which carried over to the two weeks after the treatment ended. To explain why consumption initially dropped we need not complicate the model further: once consumers see that the treatment is being implemented, they choose whether to buy a bag based on the extra utility caused by the foregone and actual donations implied by their purchasing decision. It is also easy to explain why consumers fail to respond right away: once in the shop without a bag brought from home, despite the donations, the consumers needs to decide whether to accept the utility loss caused by buying a single-use bag and not having the means to transport their shopping home.[3] However, more consideration needs to be given to the fact that consumers did not increase their consumption of single-use bags for the two weeks following the treatment. The effect in the first week after the treatment may be justified by consumers forgetting about the removal of the donations, but it reasonable to believe that by the second week the supermarket customers would have noticed the continuous absence of the donations. A plausible mechanism explaining this finding is that consumers' preferences may have changed. Having brought a bag from home for a month may have convinced supermarket customers that the utility cost of bringing a bag is lower than they expected, reshaping their reference point and hence their optimal strategy. While we cannot rule out variation in individual responses, the average treatment effect confirms that this treatment was effective at lowering consumption.

6.3.2 Framing IPCC visuals in colours

In my second chapter I presented the results from two online experiments with representative samples of the U.S. population. The experiments tested whether the choice of colours in climate visuals affects the support for policies aimed at mitigating climate change, the emotional response to climate-related information, and the level of understanding of the content of the visual.

Previous literature studied whether the information presented in the IPCC Reports was clear and presented in an effective manner from a text readability perspective (Barkemeyer et al., 2016). However, in a world in which people are exposed to large amounts of information, climate visuals can better present and summarise large amounts of complex information than text (Wardekker et al., 2008). Additionally, they can potentially promote engagement with environmental issues (Smith and Joffe, 2009), trigger emotional responses (Smith and Joffe, 2009) which may foster support for climate change policies (Nabi et al., 2018), and reduce the perceived psychological distance of climate change (Brügger et al., 2015). A crucial component of climate visualisation is the use of colours (Morelli et al., 2021),

[3] In the paper we also noted that the full treatment starts in the second week, as only from the second week we showed the receipts for the donations to the two charities around the shop.

which may hinder or facilitate graph comprehension. In the first study presented in this paper we tested whether using a uniform colour scale to present three panels of a visual affects participants' understanding, climate change perception and stated preferences for climate change policies. In the second study we tested whether the choice of colours used to represent possible future scenarios affects the same outcomes.

Participants in both experiments received the same information, but half of the respondents saw it in one colour scale and half in the other. This ensures that information is not the driver of differences in the treatment and control group. The visuals shown do not use colours used by any political party, and respondents are not invited to think about how other people may perceive the threats posed by climate change. While some respondents may perceive the data to be overstating or understating climate change as an issue, or may find the information provided by this set of scientists unreliable, there is no reason to expect this reaction to change based on the colour scale used. As participants are randomly allocated to the treatment and control conditions, identity will not be the driver of any treatment effect. Any difference in policy support due to the information provided by the visual will be captured by changes in understanding and the updating this generates.

In each study participants are shown the visual and are asked three sets of questions investigating: (*i*) their support for policies aimed at mitigating climate change; (*ii*) their perception of the dangers posed by climate change, and (*iii*) questions testing their understanding of the visual. While the third set of questions tests participants on objective information, the first and the second are subjective. Participants in the experiments are assumed to have some prior beliefs over the severity of climate change and a prior support for policies aimed at mitigating global warming. These beliefs and levels of support for policies are depend on their previous levels of information, their identity and their (perceived) understanding of climate change. Given the scientific uncertainty over climate change depicted in the visuals the participants are exposed to, let us consider stochastic consumption levels and reference points drawn according to the probability measures F_t and G_t. Consider a respondent who observes the scenarios for carbon emissions. This information can affect their perception of the severity of climate change and hence their optimal behaviours.

Before taking part in the experiment, agents maximised subjective utility. When exposed to the visual, participants receive a signal that can shift the perceived probability measures from their previous levels, and may make these distributions wider or narrower. For instance, an agent who is initially convinced that climate change will have catastrophic consequences may find some relief in seeing multiple scenarios for CO_2 emissions, some of which may be a better outcome than those imagined. Instead, someone who expects global warming to have less serious consequences may reevaluate their perception when looking at the IPCC visual. Depending on the participants' priors and the level of understanding of the figure there are many plausible preferred personal equilibria: agents with extreme prior reference points (i.e., either no or full support for a carbon tax and either no support for fuel subsidy or support for the highest possible subsidy) not to be swayed by the visuals shown to them. In the same vein, agents who better grasp the information presented in the visuals are more likely to respond to the information (for them $f(I_t, s)$ is higher). This may help explaining why we find no differences between Democrats in the treatment and control groups. Participants who identify as Democrats in both groups state the highest levels of support for policies aimed at mitigating climate change and a high level of worry for the threats posed by climate change. Even if the information provided narrowed the perceived probability measures, there would be no way of showing this change within the survey (the maximum level of support and worry are bounded by the Likert scale used in asking the questions). On the other hand, participants who identify as Republicans in the treatment group show a better understanding of climate visuals and state a higher support for a carbon tax. The average treatment effect in both studies is not significantly different from zero, and the levels of understanding between the treatment and control group are not significantly different. This is consistent with the driver considered, but might also be due to the fact that the impact of observing new data is stronger than the impact of the colours used to present it.

6.3.3 Showing Covid-19 data on different scales

In Chapter 3 I presented a paper showing that the scale chosen to represent Covid-19 data affects people's level of understanding, attitudes towards the pandemic, and policy preferences. This survey was ran during the first wave of the pandemic. At the time, mass media routinely published data depicting the evolution in the number of Covid-19 cases and deaths in a given area. Some outlets presented quantities on the Y-axis on a linear scale (The Washington Post, 2020; Lopez, 2020), while others opted for a logarithmic one (The Guardian, 2020; Financial Times, 2020; New York Times, 2020). In an online survey we tested the impact of using one or the other scale. Half of the participants in the experiment were randomly assigned to the linear group, in which they were shown the evolution of Covid-19 deaths in the U.S. on a linear scale. The other half were assigned to the log group, in which participants saw the same data, but plotted on a logarithmic scale. Respondents were asked questions about their attitudes, policy preferences and graph understanding questions.

Preferences over Covid-19 policies and attitudes are particularly interesting from a theoretical standpoint, as many people never held preferences over a pandemic before. As the health crisis caused by the pandemic worsened, people had to form beliefs over the likelihood of catching the virus based on their behaviours and form preferences over policies aimed at containing the crisis. The novelty of the crisis makes it compelling to assume that people perceived wide distributions for F_{t_0} and G_{t_0}. For instance, the average person perceived a positive probability of catching the virus, and attached a positive probability of contracting a severe case, but was unable to pinpoint them with precision, or understand the consequences that contracting the virus would entail for them. Hence their policy preferences over closing shops or mandating the use of face masks were formed in a setting with high uncertainty. The information surrounding the pandemic did not provide help to narrow these distributions. On the one hand, the news reported extreme cases, often accompanied by videos of intensive care units under stress and salient deaths. On the other hand, as the pandemic evolved, more outlets started reporting and interviewing asymptomatic patients. In this setting, the identity I_t may be the driver of action, as it can capture how the behaviours of a person's network shapes their own beliefs- where preferences over outcomes and reference points are not clear, a person may just choose to follow what people around them are doing. Some people had networks of relatively scared people, and were therefore more prone to display preventive behaviours and higher support for lockdowns, while others had relatively optimistic networks and were in favour of a more regular life. With random sampling we should expect the same distribution of these types in the treatment and the control group.

We carried out our survey in mid-April 2020, a few months after the pandemic hit worldwide and when the media provided daily information on the evolution of the pandemic. Just like in the case of Chapter 2, the observed differences run through the understanding of the data presented.

Several preferred personal equilibria can emerge. To simplify the setup, consider an agent with identity I (not changing between the two periods) assigning a decision weight (probability) $q_{t,L}$ to the pandemic being an easy event to overcome at time t, and $q_{t,H}$ to the pandemic being a disruptive crisis at time t. Preferences for lockdowns may not be monotonically increasing in $q_{t,H}$, as closing businesses has repercussions on the economic activity and may directly reduce the income of the respondent. However, a higher $q_{t,H}$

increases the likelihood of undertaking preventive behaviours. Participants in the survey need not attach the same probabilities to events, so a participant i will form preferences around $q^i_{t,L}$ and $q^i_{t,H}$, which might change when data is shown to them. Participants who look at the linear scale data and perceive the situation to be calmer than they thought will update so that $q^i_{t_1,H} < q^i_{t_0,H}$, reducing the perceived importance of behaviours and policies aimed at containing the pandemic. Participants who perceive the data to be worse than their prior will update so that $q^i_{t_1,H} > q^i_{t_0,H}$ and will perceive an increased importance of behaviours and policies aimed at containing the pandemic. Participants who perceive the data to be in line with their expectations will either not update $(q^i_{t_1,H} = q^i_{t_0,H})$ or perceive a narrower distribution, where more extreme outcomes become less plausible.

The scale of the data affects how participants update $q^i_{t,L}$ and $q^i_{t,H}$. Specifically, consider two participants, i and j, with equal identities, prior amount and understanding of information. i is randomly assigned to the linear group, while j to the logarithmic one. I assume that after being exposed to the data $q^i_{t_1,H} > q^j_{t_0,H}$ as the level of understanding of the linear scale raises $f(I, s)$. The data offers support for this hypothesis, as participants in the linear group show a better understanding of the data than those in the logarithmic group. Ceteris paribus, those who see data on the linear group perceive a worse trend for the pandemic $(q^i_{t_1,H} > q^j_{t_0,H}.)$. However, the logarithmic scale displays a higher value on the Y-axis, which might act as anchor when assessing the short-term evolution of the pandemic. Our results support this hypothesis: while participants in the logarithmic group predict more deaths in the short term, the linear group expects the crisis to last longer. Consistently, the linear group is more worried about the health crisis, but anticipates wearing masks less. Participants in the linear group also state a preference for keeping non-essential businesses closed for longer, but a lower support for closing them in the first place. While other explanations cannot be ruled out, a plausible reason for not wearing a mask as often and showing a lower support for the initial closure of business is consistent with the perception of a worsening pandemic. Not wearing a mask now allows participants to ration them for the worse imminent future. Perceiving a much worse future makes closing businesses early be perceived as an avoidable economic loss that should have not taken place given the need to close them now.

The findings in this paper suggest that scale used to represent the data may act as an involuntary nudge to consider the pandemic as more or less serious (respectively causing $q^i_{t_1,H} > q^i_{t_0,H}$ or $q^i_{t_1,L} > q^i_{t_0,L}$). They shed light on the importance of understanding and framing in the decision making process, and suggest that framing effects are especially marked in the presence of new events. As in the previous paper, these general insights do not rule out different individual responses to the data, but they suggest that the using a logarithmic scale to report data to the general public is a questionable choice.

6.3.4 Nudges to improve the acceptability of a Covid-19 vaccine passport

In Chapter 4 I presented a paper studying whether two nudges could increase the level of support for a Covid-19 vaccine passport for international travels. A vaccine passport would require people who wish to travel to show evidence of their vaccination status. We tested whether each nudge worked in isolation, their compounded effect, and whether these nudges had a negative spillover on the intention to get vaccinated.

This paper built on a previous study where we show that the status quo bias can be used to foster support for a domestic and an international travelling Covid-19 vaccine passport (Guidi et al., 2021). The first nudge we tested is the status quo bias, which posits that people are more likely to support a policy if it is perceived as a continuation of the past. Evidence for the status quo bias is abundant (Lang et al., 2021) and a theoretical underpinning of this effect with reference dependent preferences can be found in both K&T, K&R and most models of loss aversion.

In Guidi et al. (2021) we tested that communicating the existence of similar vaccine passports, e.g., the international certificate of vaccination used for the yellow fever vaccine, increases the level of support for a Covid-19 vaccine passport, both for domestic and international travel. Presenting the policy through this lens also reduces polarisation, intended as the distance between Democrats and Republicans in the level of support for the introduction of a Covid-19 passport. In the paper in the fourth chapter we replicated this finding. The second mechanism we test relies on the literature showing that peer influence can shape behaviours and attitudes (Allcott, 2011; Ayres et al., 2013). Rothschild and Malhotra (2014) find that this is also the case with stated behaviours, showing that poll results can influence individual-level attitudes and trigger a “bandwagon effect”. Hardmeier (2008) further shows that when polls indicate that a policy is widely supported, even more people will be persuaded to support it. In this paper we leveraged this finding and informed participants that data from a recent poll showed that only a third of Americans believe that the Covid-19 vaccine passport should not be introduced.

Participants in this experiment were randomly assigned to one of four groups: a control group, a status quo group, a peer effects group, and a status quo + peer effects group. In the experiment, we asked respondents about their vaccination status before providing any information and asked respondents who had not yet completed their cycle whether they intended to do so. Similarly, we asked respondents who had not received a vaccine whether they intended to get vaccinated. All respondents received general information on the vaccine passport. Participants in the control group only saw this information. Participants in the status quo group saw this information and information on the existence of similar vaccine passports. Participants in the peer effects group saw this information and information on the current amount of support for a vaccine passport. Finally, participants in the last group saw all the previous information. Participants were asked their support for the pass, and whether they would be likely to get the vaccine if a pass was introduced.

The structure of the treatments allows to conceptualise the paper within the same framework used in the previous section. Participants are assumed to hold some priors over the likelihood of contracting Covid-19, its severity, and the desirability of an international vaccine passport. These priors are influenced by the participants' information and identity. Unlike in the previous sections, the treatment effect is not driven by participants' understanding of the information or their identity, but the information they receive.

All respondents received basic information on the features and the purpose of a Covid-19 passport for international travel. Those in the status quo group were also informed that requiring proof of vaccination for international travel is not unprecedented. They were also shown a picture of the International Certificate of Vaccination or Prophylaxis. Respondents in the peer effects group were informed that only one third of Americans oppose the introduction of a Covid-19 vaccine passport. Last, respondents in the status quo + peer effects group saw information on the existence of similar vaccine passports and were told about the percentage of Americans opposing the introduction of a Covid-19 vaccine passport.

Respondents in the status quo group, in the peer effects group and those who receive both nudges saw more information than those in the control group. The information provided did not concern the pass itself, and in traditional models of consumer theory it should be irrelevant in determining preferences. However, learning about the existence of similar vaccine passports might lead respondents to perceive the passport differently. Similarly, learning that only a minority of people in their country are against its introduction may induce them to state a higher support for the passport. Consider a participant who is agnostic about the introduction of the Covid-19 vaccine passport, is not sure about the general level of support surrounding the proposal and is unaware of the existence of similar documents. Reading about the existence of similar vaccine passports nudges the agent to consider this new version feasible. Additionally, the lack of information about previous passports of this sort can now interpreted positively, as an absence of scandals concerning its use. Similarly, reading that only a small minority of citizens is against the introduction of a Covid-19 vaccine passport, might make the agent perceive that being in favour of the passport means reducing their distance from their target identity. Participants who see both information update twice. First, because of the information provided to the status quo group, and again following information about the level of support for the passport, with the posterior beliefs implied by the first treatment becoming the priors of the second one.

Participants in the status quo group perceived a higher importance of the vaccine passport than in the control group. They also perceived the pass to be less unfair, and stated a higher support for the introduction of a Covid-19 vaccine passport. Participants in the peer effects treatment also stated a higher perceived importance of the passport and a higher support for its introduction, but this treatment had a limited impact on the perceived unfairness. The two nudges showed weak additionality in their impact, with participants in the status quo + peer effects group attaching a higher importance to the pass than those in the other treatment groups, stating the lowest level of perceived unfairness and showing a higher support for the introduction of a Covid-19 vaccine passport. This is consistent with a double updating following the two sets of information. Overall, there was no evidence of a spillover from the treatments to the likelihood of getting a vaccine, but this might be because most of the participants stated a high likelihood to get the vaccine in the first place.

6.4 Limitations

While the model I presented in this chapter is flexible and allows to capture heterogeneity in treatment effects, its flexibility comes at the cost of not being directly estimable. I am unable to provide a functional form for $f(I_t, s)$ and hence cannot measure in an exact way the impact of leveraging understanding or identity on their own in fostering pro-social behaviours. I also lack information on participants' priors that would allow me to estimate individual treatment effects. More work is needed to capture decisions that are inter-related. For instance, if the results in the fourth chapter suggested that the use of two nudges caused a crowding out effect instead of additionality, the model would be unable to capture how the reasoning behind the result. Considering a utility function that is additive and separable in its components makes it relatively straightforward to discuss comparative statics and show how changes in prices or information provision can affect choices, but fails to capture behaviours and consumption choices that are complementary to the utility of an agent. For instance, in the fifth chapter of this thesis I presented a paper studying how different sources of worry compete in people's minds. The results of that paper cannot be framed into this theory and deserve further work.

6.4.1 Non-separable consumption and worries in EU countries

In Chapter 5 I presented a paper investigating how different sources of concern interact in people's mind using survey data from the Eurobarometer. A dynamic model was employed to study their interactions and allow asymmetric relationships among the concerns. We show that an increase in the concern for the environment often favours the growth of concerns for the economy, while higher concerns for the economy and for other sources of worry often push down concerns for the environment. In the context of my theoretical model these sources of worry can only be interpreted as perfect substitutes with different marginal utilities. The model allows me to capture changes in the share of worries over time, as preferences are assumed to be time-dependent. For instance, the 2008 economic crisis might make the economic situation more salient, at the expense of other sources of worry. Equally, the environmental crisis we are currently facing might trigger worries for the economy. However, the current specification does not allow me to capture asymmetric interactions. Consider two worries i and j. The dynamic model used in Chapter 6 allows to capture instances in which an increase in i favours increases in j, but an increase in j negatively affects i. With separable utility I cannot capture this in my theoretic model. Further work is needed to allow spillovers between the demand of a good and that of another and to allow these relationships to be asymmetric. One could imagine a model in which the cross-elasticity between stating the economy or other worries is negative (that is, as concerns for the economy grow, concerns for other issues decrease), while the cross-elasticity between other sources of worry and the economy is positive (so that once concerns for other sources of worry increase, concerns for the economy also grow). This would require a different model specification and dropping the separability assumption, but this would come at the expense of losing the simplicity of exposing the model, and so is left as a future exercise.

6.5 Conclusions

This chapter provides a theoretical foundation to the papers in this thesis. The two-period model of reference-dependent preferences presented accounts for the direct utility of consumption and a gain-loss component from a reference point at a given time. The model is applicable to consumption decisions as well as stated preferences. I introduced a way to conceptualise an experimental treatment (a signal) and showed how heterogeneous priors and biased updating can explain heterogeneity in participants' responses to signals. The identity of a participant, their level of understanding and the information they have directly affect how they process the signals they receive and considerations over these mechanisms should be given in the design phase of a behavioural intervention. The model also allows me to conceptualise stochastic consumption levels and reference points. This is crucial in the context of climate change and the recent pandemic, and applies to any decision environment with scientific uncertainty, where people can only try to maximise utility subject to their perceived probability measures. My contribution is to extend previous work on loss aversion and provide a generally applicable and tractable model of consumer choice. However, there remains work to do to make the model directly testable and to allow for correlations between consumption choices.

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6.A Appendix

6.A.1 Proof of Proposition 1

This proof replicates the proof presented in K & R.

1. Follows from the definition of F and G.
2. This can be proven by contradiction. Suppose that $u(c,c') \geq u(c',c')$ and $u(c,c) \leq u(c',c)$. Using the definition given for the utility function and adding these two inequalities implies $m(c)+m(c')+n(c|c')+n(c'|c) \geq m(c)+m(c')+n(c|c)+n(c'|c)$. We can eliminate $m(c)+m(c')$ from both sides and notice that $n(c|c)+n(c'|c') = 0$. This implies, by definition of $n(\cdot)$ that $\sum_{k=1}^{K}[\mu(m_k(c_k)-m_k(c'_k))+\mu(m_k(c'_k)-m_k(c_k))] \geq 0$. If $c' \neq c$ using A3 this is a contradiction of loss aversion.
3. To prove this it is sufficient to prove that for any $F, F' \in \Delta(\mathbb{R}^K)$ we have $U(F|F)+U(F'|F') > U(F|F')+U(F'|F)$. Let F_k and F'_k denote the marginals of F and F' on dimension k. The expected consumption utilities are equal on both sides, so it is sufficient to prove that the above holds for the gain-loss utility:

$$\begin{aligned}\int\int \mu(m_k(c_k)-m_k(r_k))dF_k(c_k)dF_k(r_k)+\int\int \mu(m_k(c_k)-m_k(r_k))dF'_k(c_k)dF'_k(r_k)\\ \geq \int\int \mu(m_k(c_k)-m_k(r_k))dF_k(c_k)dF'_k(r_k)+\int\int \mu(m_k(c_k)-m_k(r_k))dF'_k(c_k)dF_k(r_k)\end{aligned} \tag{6.3}$$

for all k. The inequality is strict for $F_k \neq F'_k$ and holds with equality when the marginals are equal ($F_k = F'_k$). We can establish this easily using a μ that satisfies the modified version of A4 where for all $x \neq 0$ $\mu''(x) = 0$. Then there exists and $\alpha > 0$ such that for any $x \in \mathbb{R}$ we have $\mu(x)+\mu(-x) = -\alpha|x|$. Using this and dividing by $\frac{\alpha}{2}$ the above becomes:

$$\begin{aligned}\int\int |m_k(c_k)-m_k(r_k)|dF_k(c_k)dF_k(r_k)+\int\int |m_k(c_k)-m_k(r_k)|dF'_k dF'(r_k)\\ < 2\int\int |m_k(c_k)-m_k(r_k)|dF_k(c_k)dF'_k(r_k)\end{aligned} \tag{6.4}$$

For real values of x, a, b let $x \in ((a,b))$ denotes that x is between a and b such that

$x \in (a,b)$ if $a < b$ and $x \in (b,a)$ if $b < a$. Let $I(\cdot)$ denote the indicator function. Then the inequality can be rewritten as

$$\int\int\int I[(x \in ((m_k(c_k), m_k(r_k)))]dxdF_k(c_k)dF_k(r_k)$$
$$+\int\int\int I[x \in ((m_k(c_k), m_k(r_k)))]dxdF_k'(c_k)dF_k'(r_k)$$
$$< 2\int\int\int I[x \in ((m_k(c_k), m_k(r_k)))]dxdF_k(c_k)dF_k'(r_k) \quad (6.5)$$

Reversing the order of integration gives

$$\int Pr_{c_k \approx F_k, r_k \approx F_k}[x \in ((m_k(c_k), m_k(r_k)))]dx$$
$$+ Pr_{c_k \approx F_k', r_k \approx F_k'}[x \in ((m_k(c_k), m_k(r_k)))]dx$$
$$< 2Pr_{c_k \approx F_k, r_k \approx F_k'}[x \in ((m_k(c_k), m_k(r_k)))]dx \quad (6.6)$$

This is weakly true point by point and strictly on a set of positive measure. Let $F_k(m_k^{-1}(x)) = p(x)$ and $F_k'(m_k^{-1}) = p'(x)$. Notice that if $F_k \neq F_k'$, there is a set of positive measure such that $p(x) \neq p'(x)$. The probability that x is on a line segment of two points $m_k(c_k)$ and $m_k(r_k)$, where c_k and r_k are chosen independently according to F_k' is $2p'(x)(1-p'(x))$ and the probability that it is between two such points when c_k and r_k are chosen according to F_k and F_k' is $p(x)(1-p'(x)+p'(x)(1-p(x))$. It sufficient to prove that $p(x)(1-p(x)) + p'(x)(1-p'(x)) \leq p(x)(1-p'(x)) + p'(x)(1-p(x))$ and that the inequality is strict for a set of positive measures. This is true since $(p(x)-p'(x))^2 \geq 0$ and the inequality is strict whenever $p(x) \neq p'(x)$

6.A.2 Proof of Proposition 2

This proof replicates the proof for Proposition 3 presented in K & R. Without loss of generality, let $\mu(x) = \eta x$ for $x > 0$ and $\mu(x) = \eta\lambda x$ for $x \leq 0$. Suppose $c \in argmax_{c' \in D^*} m(c')$. For all $c' \in D^*$:

$$\sum_{k: m_k(c_k') > m_k(c_k)} [m(c_k') - m(c_k)] \leq \sum_{k: m_k(c_k') < m_k(c_k)} [m(c_k) - m(c_k')] \quad (6.7)$$

Using the fact that $m(c') < m(c)$:

$$u(c'|c) = m(c') + \sum_k \mu(m(c'_k) - m(c_k)) \leq m(c) + \sum_k \mu(m(c'_k) - m(c_k))$$
$$= m(c) + \eta \sum_{k:m_k(c'_k)>m_k(c_k)} [m(c'_k) - m(c_k)] - \eta\lambda \sum_{k:m_k(c'_k)<m_k(c_k)} [m(c_k) - m(c'_k)]$$
$$\leq m(c) = u(c|c) \quad (6.8)$$

To show that c is a PPE, it is sufficient to prove that it is preferred ex ante to all feasible choices within the decision maker's choice set. We show that for any distribution F over D^*, we have $U(F|F) \leq \int m(c')dF(c')(\leq m(c))$ This can be proven by dimension. The gain-loss utility part of $U(F|F)$ in dimension k is

$$\frac{1}{2}\int\int [\mu(m_k(c_k) - m_k(r_k) + \mu m_k(r_k) - m_k(c_k))]dF_k(c_k)dF_k(r_k) \quad (6.9)$$

By assumption A3, this is non-positive. Finally, to show that a lottery F that is non-deterministic or does not maximize $m(\cdot)$ is not a PPE, we show that c is strictly preferred to these outcomes ex ante. This is obvious for deterministic outcomes that do not maximize $m(\cdot)$. And for a non-deterministic F_k, Expression (9) is strictly negative, establishing the claim for that case as well.