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Do economic preferences predict pro-environmental behaviour?

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Abstract

Understanding the determinants of pro-environmental behaviour is key to address many environmental challenges. Economic theory and empirical evidence suggest that human behaviour is determined by people's preferences over risk, time, and social consequences. As such, individual differences in these preferences should predict individual differences in pro-environmental behaviour. In a pre-registered study, we measure economic preferences in seven domains (risk taking, patience, present bias, altruism, positive reciprocity, negative reciprocity, and trust) and test whether these preferences predict pro-environmental behaviour in everyday life measured using the day reconstruction method. We find that only altruism is significantly associated with everyday pro-environmental behaviour. This suggests that people recognise everyday pro-environmental behaviours to be beneficial to others, but do not integrate the riskiness, inter-temporal structure, nor other social characteristics of pro-environmental behaviour into their decision-making. We also show in an exploratory analysis that different clusters of everyday pro-environmental behaviours are predicted by patience, positive reciprocity, and altruism, indicating that these considerations are relevant for some, but not other, pro-environmental behaviours.

Keywords: Time preferences; risk preferences; social preferences; pro-environmental behaviour; day reconstruction method.

Declarations of interest: none.

1. Introduction

It is essential to limit global warming to 1.5°C above pre-industrial levels to decrease the risk of irreversible climate change and loss of ecosystems (Hoegh-Guldberg et al., 2018). Researchers, practitioners, and policymakers alike have suggested various strategies to achieve this goal, and behavioural change is a key component of many of these strategies. Of particular importance is the encouragement of pro-environmental behaviours in people's everyday lives (Hoegh-Guldberg et al., 2018; Ockwell, Whitmarsh, & O'Neill, 2009; OECD, 2017; Stern, 2007). Pro-environmental behaviours are those actions that avoid environmental 'bads', such as CO_2 emissions or plastic pollution (Steg & Vlek, 2009). Examples of pro-environmental behaviour include conserving water and electricity, recycling, choosing sustainable transport options and avoiding food items with high environmental footprints.

Designing policies that effectively encourage pro-environmental behaviour requires an understanding of the determinants of this behaviour. One way to identify these determinants is to find out why some people act environmentally friendly while others do not, i.e. to analyse inter-individual differences. Economics and other social sciences assume that individual differences in people's tendencies to take risks, delay rewards, and act pro-socially can explain why people behave differently. Economics formalises these factors as individual risk, time, and social preferences (DellaVigna, 2018). The present paper therefore tests whether individual economic preferences predict pro-environmental behaviour in everyday life.

Empirical evidence suggests that risk, time, and social preferences predict a wide range of behaviours. For example, risk preferences predict people's investment choices, occupation, and health behaviours (Anderson & Mellor, 2008; Bonin, Dohmen, Falk, Huffman, & Sunde, 2007; Dohmen et al., 2011); time preferences predict credit card borrowing and credit worthiness (Meier & Sprenger, 2010, 2012), and social preferences predict charitable giving (DellaVigna, List, & Malmendier, 2012). Despite these findings, there is an ongoing discussion regarding the predictive power of economic preference and their importance relative to contextual and situational factors (Cohen, Ericson, Laibson, & White, forthcoming; Galizzi & Navarro-Martinez, 2018; Goeschl, Kettner, Lohse, & Schwieren, 2020; Levitt & List, 2007; Mata, Frey, Richter, Schupp, & Hertwig, 2018).

There are good reasons to expect economic preferences to be associated with pro-environmental behaviour. Pro-environmental behaviours typically generate uncertain benefits, suggesting links to risk preferences. Indeed, previous research suggests that risk averse people are less likely to invest in energy efficient technology (He, Jin, Gong, & Tian, 2019; Qiu, Colson, & Grebitus, 2014). Pro-environmental behaviours are usually costly in the present and beneficial in the future, hinting at the importance of time preferences. Empirical work does find that lower discount rates predict higher investments in energy efficiency (Fuerst & Singh, 2018; Newell & Siikamäki, 2015). Pro-environmental behaviours also impose positive externalities on others, implying links to social preferences (Handgraaf, Griffioen, Willem, & Thøgersen, 2017). People with stronger altruistic preferences have been shown to be more likely to adopt green electricity programmes (Clark, Kotchen, & Moore, 2003; Kotchen & Moore, 2007). However, the literature also documents null results and, in some cases, contradictory results (Bradford, Courtemanche, Heutel, McAlvanah, & Ruhm, 2017; Goeschl et al., 2020; Paladino, 2005; Schleich, Gassmann, Meissner, & Faure, 2019), suggesting that a more systematic investigation of the links between economic preferences and pro-environmental behaviour is needed.

There are several reasons that could potentially explain the contradictory results in the literature. First, recent research on the links between economic preferences and pro-environmental behaviour tends to focus on a single pro-environmental behaviour as predicted by a single preference domain. Significant associations in these studies might be explained by the riskiness, timing, or social aspects of the behaviour in question, and it might be irrelevant whether the behaviour is pro-environmental or not. Second, many pro-environmental behaviours may be associated with risk, time, and social preferences simultaneously, and studies may or may not control for the other preference measures. For example the future is uncertain (Andersen, Harrison, Lau, & Rutström, 2008) and short-term temptations to be selfish may conflict with better judgments to act pro-socially (Martinsson, Myrseth, & Wollbrant, 2012). Third, focusing on a single pro-environmental behaviour likely ignores a large range of small-scale, frequent everyday behaviours linked to people’s lifestyles. These behaviours can have massive environmental impact once aggregated as their impact accrues over time.

To overcome these limitations, the present paper presents a systematic, pre-registered test of whether seven economic preference measures predict a large number of pro-environmental behaviours enacted in people’s everyday lives. We construct several indices measuring the extent and intensity of pro-environmental behaviour as using these aggregate indices avoids identifying correlations driven by the riskiness, timing, or social elements of single behaviour. We conduct ceteris-paribus analyses predicting pro-environmental behaviours by all preferences simultaneously to identify the effect of one preference measure while controlling for other preferences. Finally, we measure a large battery of pro-environmental behaviours in everyday life to capture the high-frequency behaviours, linked to people's lifestyles that can add up to large environmental impacts. This approach also allows to identify clusters of pro-environmental behaviours.

Participants in our online survey (N = 349) first completed measures of seven economic preferences (risk taking, patience, present bias, positive reciprocity, negative reciprocity, altruism, and trust) using experimentally validated survey items (Falk et al., 2018; Falk, Becker, Dohmen, Huffman, & Sunde, 2016). Participants then reconstructed their previous day using a technique that facilitates recall (the day reconstruction method as developed by Kahneman, Krueger, Schkade, Schwarz, & Stone, 2004) and reported the pro-environmental behaviours they engaged in yesterday. We first calculated the number of pro-environmental behaviours participants had engaged in the day prior to the study as a proxy for the extent of pro-environmental behaviour in daily life. We also calculated the ratio of enacted pro-environmental behaviours over the number of situations where a pro-environmental behaviour was possible to acknowledge that not every participant had the same number of opportunities to engage in pro-environmental behaviour. This provided us with a proxy for the intensity of pro-environmental behaviour yesterday. Additionally, we elicited participants' general tendencies to engage in pro-environmental behaviours as well as their pro-environmental investment decisions.

The results from the pre-registered analysis show that only altruism predicts the number of pro-environmental behaviours participants engaged in yesterday. Altruism also predicts people's general tendency to act pro-environmentally as well as the number of green investments made. None of the preference measures predict the ratio of the number of enacted pro-environmental behaviours over the number of situations where a pro-environmental behaviour was possible. An exploratory principal components analysis suggests that we captured four distinct clusters of everyday pro-environmental behaviours: eco-shopping behaviours; electricity and water saving behaviours; awareness behaviours; and efforts to reduce waste and consumption. Altruism predicts eco-shopping behaviours, positive reciprocity predicts electricity and water saving behaviours, and patience predicts awareness behaviours. All other preferences are unrelated to the four clusters.

Our findings contribute to the increasing literature exploring links between economic preferences and pro-environmental behaviour by suggesting that social preferences, and in particular altruism, but not risk and time preferences, are associated with pro-environmental behaviour. Moreover, we present evidence suggesting that the diverse range of everyday pro-environmental behaviours comprises four distinct clusters, which differ in their relation to individual economic preferences. It is worth further considering the structural differences in decision making across these four clusters of pro-environmental behaviours in future research, as they may explain the disparate links to people's preferences and, relatedly, the contradictory results in the existing literature. The findings can also be interpreted as a test of the external validity of the preference measures. The overall relatively weak relation to pro-environmental behaviour in everyday life highlights the need to investigate the role of further individual and situational factors, including the domain-specific preference measures.

The remainder of the paper is structured as follows. Section 2 presents the methods and hypotheses. Section 3 presents the pre-registered and exploratory results. Section 4 concludes with a discussion.

2. Material and methods

2.1. Participants and procedures

We recruited 350 participants to take part in an online study via Prolific Academic (https://www.prolific.co/). The study was approved by the University College Dublin Human Research Ethics committee and informed consent was obtained from all participants. We staggered recruitment over seven consecutive days, collecting 50 responses per day. In order to take part, participants had to be registered with the recruitment service, be over 18 years of age, resident in the UK, and must not have participated in a pilot test of the study. Participants received £2.50 for completing the survey. One participant did not provide data on the key measures, and therefore we analyse a sample of 349 participants.

The sample mean age was 37.03 (*SD* = 12.90), 63.30% were female, 36% were single and 55% married or cohabiting, 43.3% had at least a college degree, and the mean household size was 2.93 (*SD* = 1.36), and 62% of the sample reported an individual income of less than £2000 per month. The self-reported mean math proficiency was 6.74 (*SD* = 2.80) on a scale from 0 to 10. Tables S1.1 and S1.2 in the Supplementary Information provides more details about the sample demographics.

The online survey comprised three parts: In Part 1, participants completed the economic preference measures. Part 2 contained the Day Reconstruction Method used to measure the pro-environmental behaviours that participants had engaged in on the day before the study. Part 3 asked participants to answer additional questions on how frequently they engage in pro-environmental behaviours in general how many green investments they have made in the past, psychological survey measures, and their socio-economic background. All participants completed the measures in the same order. The Supplementary Information S1-3 summarise all variables we measured.

2.2. Economic preference measures

We measured participants' risk preferences, time preferences (patience and present bias), and social preferences (positive reciprocity, negative reciprocity, altruism, and trust) following Falk et al. (2018). Their approach combines quantitative and qualitative survey questions for each preference type. For example, the risk-preference measure combines a hypothetical lottery choice sequence, where people choose five times between a safe and a risky but potentially better option, with a self-assessment about the willingness to take risks in general. For each preference measure, we first computed the z-scores of the underlying survey items at the individual level and then computed the weighted average of these z-scores using the weights from an experimental validation procedure (Falk et al., 2016). In line with Falk et al., (2018), we then standardised this weighted measure again to obtain preference measures with a mean of zero and a standard deviation of one. We added one additional set of questions to measure present bias because this economic measure of self-control and procrastination is of particular interest given its potential role in explaining intention-behaviour gaps (Kollmuss & Agyeman, 2002). We present the detailed description of the survey items and the weights in the Supplementary Information S2.

2.3. Pro-environmental behaviour measures

To measure pro-environmental behaviours in everyday life, we used the day reconstruction method (Kahneman et al., 2004). This method was designed to collect information on how people feel and what they do in their daily lives. In our study, participants first completed a short diary of yesterday that helped them to systematically reconstruct what happened during the day prior to the study. We asked participants to divide their previous day into three phases reflecting the morning, the afternoon, and the evening, and participants wrote a few words about what they did and how they felt in diary boxes we provided. In a second step, we showed participants the diary boxes again and asked them to go through their day chronologically from morning to evening to answer follow-up questions specific to the different parts of the day. Since we have 349 participants, we have data for 1047 phases of the day.

The most important follow-up questions dealt with pro-environmental behaviours. For each of the three phases, we asked the participants whether they had enacted 20 pro-environmental behaviours, such as saving electricity, reducing heating, using public transport, and car-pooling (Figure 2 in section 3.1 lists all 20 behaviours). We included behaviours that are commonly used in research on pro-environmental behaviour in everyday life (Bissing-Olson, Fielding, & Iyer, 2016; Blankenberg & Alhusen, 2018; Schmitt, Aknin, Axsen, & Shwom, 2018; Whitmarsh & O'Neill, 2010). The answer options were "*Yes*", "*No, but I could have*", and *"Not applicable or can't recall"*.

Our first measure of everyday pro-environmental behaviour is the sum of pro-environmental behaviours that participants had enacted yesterday (SUM_{Y}). Since we asked for 20 behaviours in each of the three phases (morning, afternoon, and evening), this measure ranged from 0 to 60. An alternative measure sometimes used in the literature on pro-environmental behaviour is the ratio (RTO_{Y}) of the sum of enacted pro-environmental behaviours over the sum of situations where a pro-environmental behaviour was feasible (Binder & Blankenberg, 2017; Bissing-Olson et al., 2016). We calculated this ratio for each participant as the sum of *"Yes"* answers divided by the sum of "*Yes*" or "*No, but I could have*" answers combined, which provided a range from 0 (none of the possible behaviours was enacted) to 1 (all possible behaviours were enacted).

We used the day reconstruction method because it provides details about the otherwise difficult to observe behaviours of everyday life and in particular the high-frequency pro-environmental decisions that are difficult to measure using common surveys and experiments (Lades, Martin, & Delaney, 2019). The method allowed us to measure pro-environmental behaviours as enacted in everyday life in an effective way with minimal recall bias. The day reconstruction method has been used extensively in economic and psychological research (Daly, Baumeister, Delaney, & MacLachlan, 2014; Delaney & Lades, 2017; Diener & Tay, 2014; Doyle, Delaney, O'Farrelly, Fitzpatrick, & Daly, 2017; Knabe, Rätzel, Schöb, & Weimann, 2010). It provides data comparable to other experience sampling methods, but places a lower burden on participants (Dockray et al., 2010; Kim, Kikuchi, & Yamamoto, 2013; Sonnenberg, Riediger, Wrzus, & Wagner, 2012).[1]

Additionally, we measured pro-environmental behaviour that was not specific to yesterday in two ways. Firstly, we measured participants general tendency to act pro-environmentally (*GEN*) using a list of 23 behaviours, such as energy conservation efforts or buying products with less packaging. Participants rated the frequency with which they engage in these behaviours on a scale from 1 ("*Never*") to 4 ("*Very often*"), and we calculated the average of these answers (see Table S1.1 and Figure S1.1). Secondly, we asked participants when they had last taken eight investments to reduce environmental impact (*INV*). We coded the answers as 0 if they had never taken the action or 1 if they had taken the action in the past. For each participant, we then calculated the sum of investments (see Table S1.1 and Figure S1.2).

2.4. Analysis strategy

Based on the previous literature, we pre-registered seven directional research hypotheses on the associations between economic preferences and pro-environmental behaviours. We predicted that higher levels of risk-taking and present bias would be associated with fewer pro-environmental behaviours and that higher levels of patience, positive reciprocity, negative reciprocity, altruism, and trust would be associated with more pro-environmental behaviours. To test these hypotheses, we specified the following regression models:

$$\boldsymbol{Y_i} = \beta_0 + \beta_1 RiskTaking_i + \beta_2 Patience_i + \beta_3 PresentBias_i + \beta_4 PosReciprocity_i \\ + \beta_5 NegReciprocity_i + \beta_6 Altrusim_i + \beta_7 Trust_i + \boldsymbol{X}_i + \epsilon_i$$

where $\boldsymbol{Y_i}$ represents the vector of the measures of pro-environmental behaviour (SUM_{Y}, RTO_{Y}, *GEN*, *INV*) for individual i. The independent variables include the seven standardised preference measures as suggested by their names. The vector $\boldsymbol{X}$ represents the control variables age, gender, relationship status, household size, income, self-reported math proficiency, and a day-of-the-week. ϵ is the error term. To test for associations between the preference measures

[1] An alternative naturalistic monitoring tool is experience sampling. Experience sampling studies ask participants to respond to short surveys on their mobile phones in their normal everyday lives for several times per day and several days in a row. There are many benefits of this method, but one shortcoming is that the surveys need to be relatively short. For example, Baumgartner, Langenbach, Gianotti, Müri, & Knoch, (2019) asked participants in an experience sampling study to indicate whether they had shown five pro-environmental behaviours (not littering in the street; separating waste; not buying products that are not environmentally friendly; paying attention to using little water; and ordering coffee in a reusable cup rather than a paper cup) since the last time they had answered the survey.

and SUM_Y and *INV*, we used Poisson models, representing the count-data structure of these two dependent variables. To predict RTO_Y and *GEN*, we used ordinary least squares regressions. In order to control for the multiple hypotheses that we test, we use the conservative Bonferroni adjustment and interpret associations as significant if their p-value is below 0.05/7 = 0.007143.

Before the start of the data collection, we preregistered our hypotheses, study design and analysis plan (see https://osf.io/r8vpc/). A small number of deviations from the preregistered estimation model were necessary.[2]

3. Results

3.1. Descriptive statistics and correlations

Figure 1 presents the histograms of the seven economic preference measures that are the main predictors in this paper. The first row in Figure 1 presents the distributions of risk and time preferences and the second row presents the distributions of the social preference measures.

[2] We had pre-registered to control for the number of opportunities participants had in the three phases when predicting RTO_Y. However, RTO_Y is defined as the number of pro-environmental behaviours divided by the number of opportunities, and thus already accounts for the number of opportunities. Moreover, we do not present the multi-level regressions that we had pre-registered in the main text because (i) they do not provide additional insights (see Table S12) and (ii) the data is not well-suited to analyse the person/situation interactions as we measured situational variables (e.g. who participants interacted with) across a relatively long part of the day (e.g. the whole morning) and hence did not have sufficiently specific information. Finally, we do not present the associations between pro-environmental behaviour and green identity and trait self-control as presenting these findings would distract from the paper's main message.

Figure 1 Histograms of the (standardised) economic preference measures.

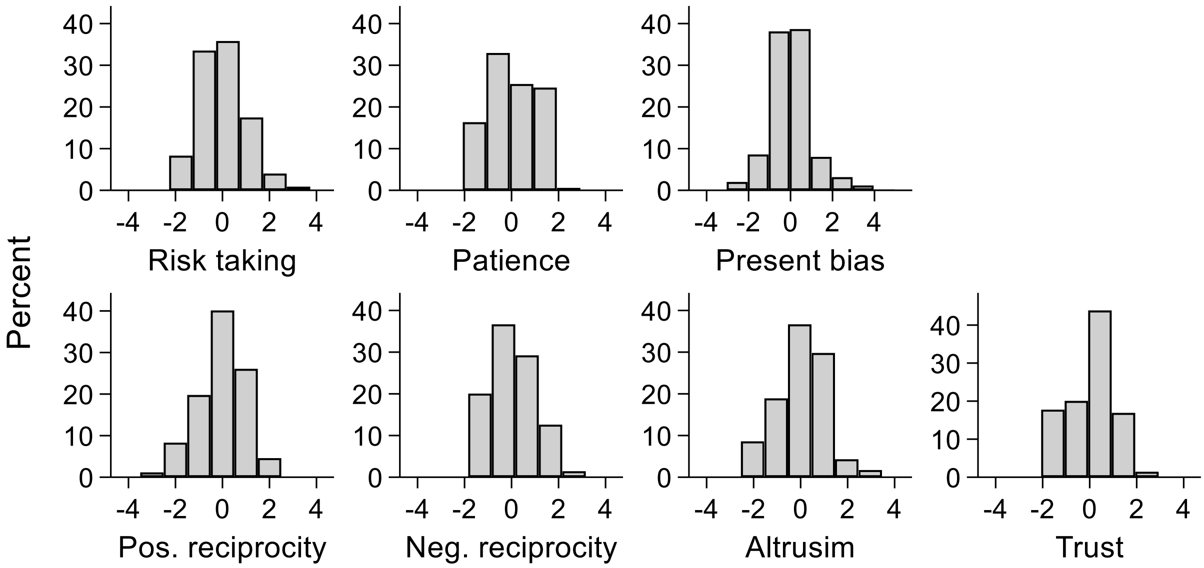


Figure 2 shows which pro-environmental behaviours were enacted more frequently than others. For example, participants indicated that they saved electricity in the house in 75% of the 1047 phases and buying environmentally friendly products was mentioned in only 7% of the phases. Participants indicated that they enacted 30% of all behaviours. The figure also shows when participants indicated that they did not enact the behaviour although it was feasible to enact the behaviour. Overall, this was the case in 18% of the behaviours, but some behaviours were more likely than others not to be enacted although feasible. For example, participants did not save electricity in the house although it was feasible in 8% of the phases and they did not educate themselves although it was feasible in 35% of the phases. The ratio between enacted behaviours and feasible behaviours tells us that saving electricity in the house was enacted more than 90% of the time when it was feasible, and participants educated themselves about the environment in only 17% of the phases when it was feasible. Car-pooling was the behaviour that was least often feasible.

Figure 2 Pro-environmental behaviours.

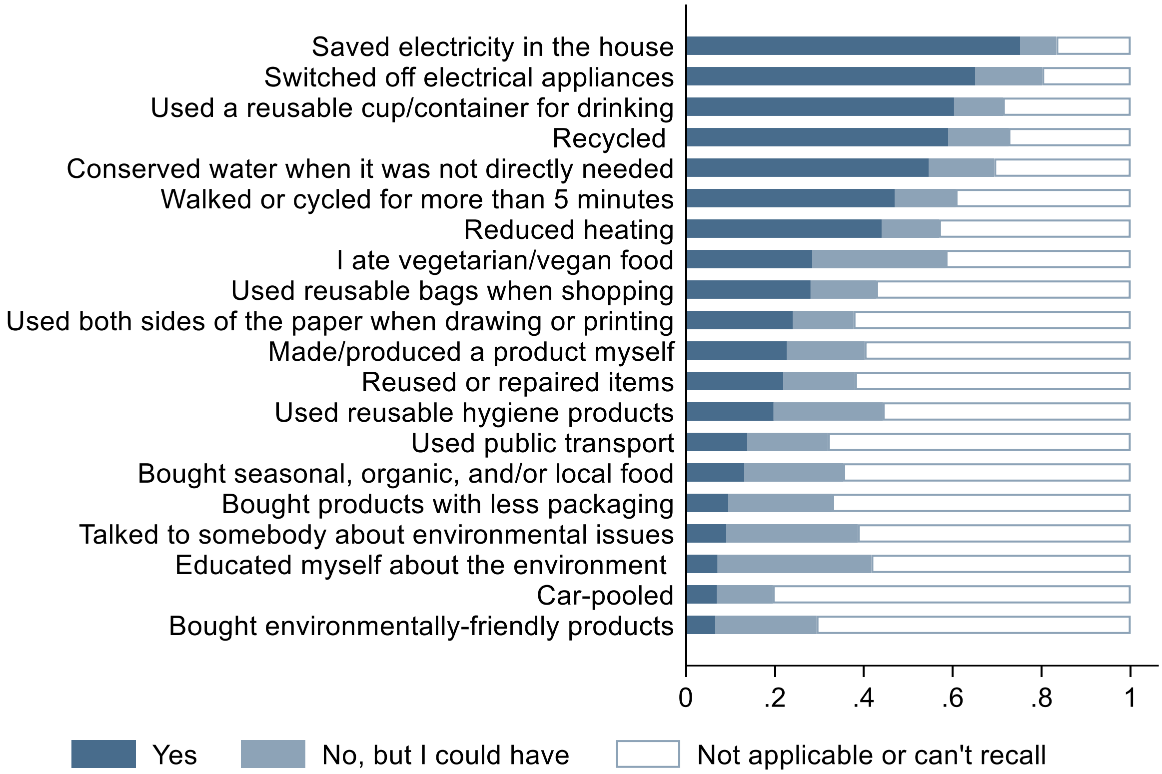


Figure 3 presents the histograms of our outcome measures of pro-environmental behaviours. Panel A shows the distribution of our main outcome measure (SUM_Y) which is the sum of pro-environmental behaviours enacted yesterday. On average, participants enacted 18.5 pro-environmental behaviours yesterday (SD = 8.44). Panel B shows the ratio of enacted behaviours over feasible behaviours yesterday (RTO_Y). On average, participants indicated that they enacted 69% of all feasible pro-environmental behaviours (SD = 25%), and 14% of the participants reported enacting all feasible pro-environmental behaviours (explaining the spike at $RTO_Y = 1$). Panel C presents the distribution of the general tendency to act pro-environmentally *(GEN)*, showing that most participants enact pro-environmental behaviours occasionally or often (M = 2.40, SD = 0.36; Cronbach's α = 0.83). Panel D shows that participants invested on average in about three products that reduce the environmental impact and home improvements (M = 2.87, SD = 1.69).

Figure 3 Distribution of the four measures of pro-environmental behaviour.

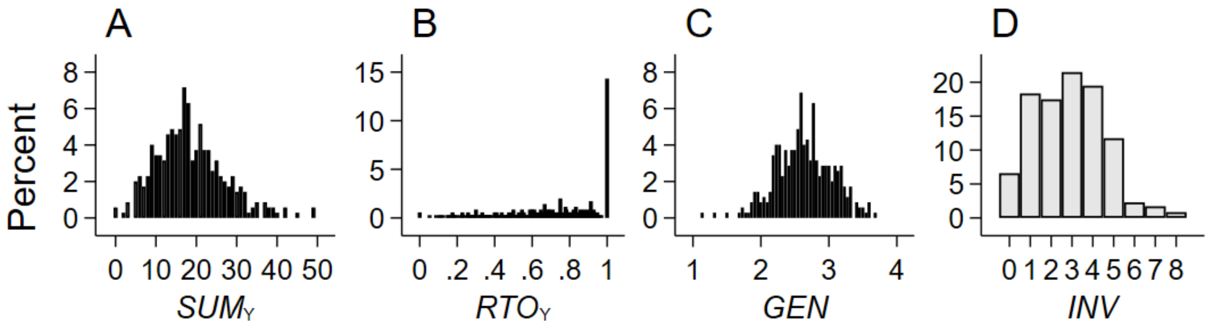
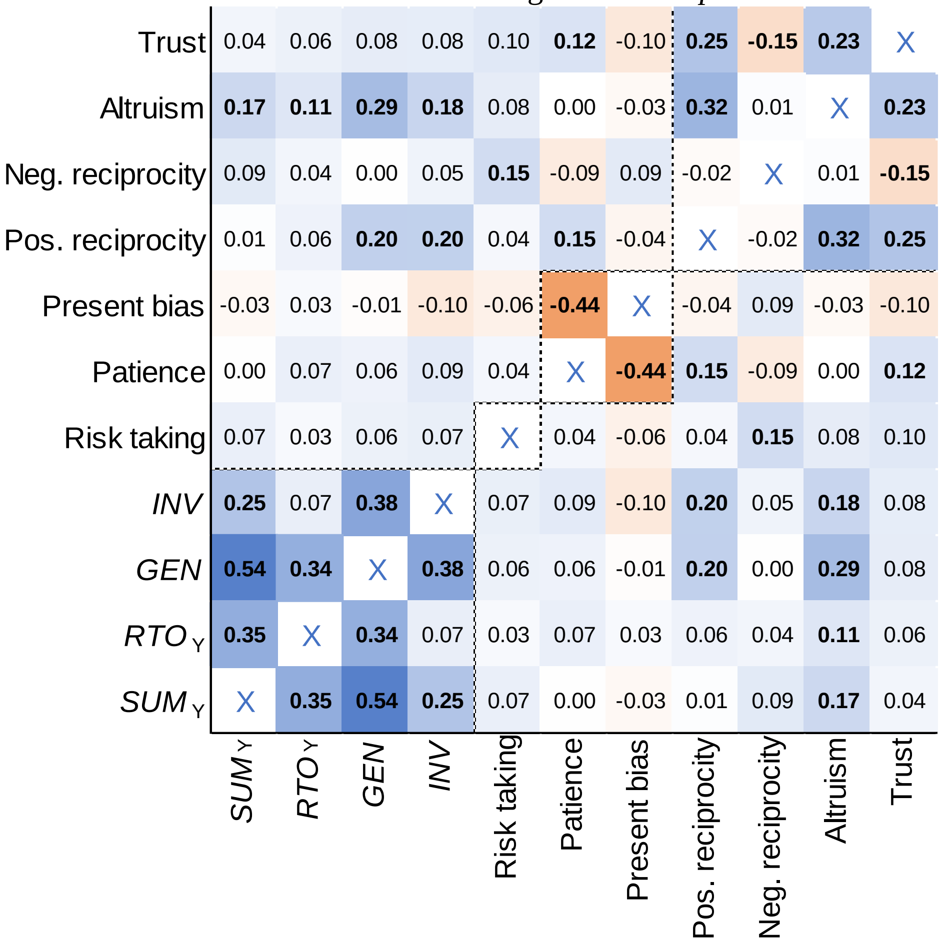


Figure 4 presents the zero-order correlations between the seven economic preference measures and the four measures of pro-environmental behaviour. The figure shows that some preference measures are significantly correlated with other preferences measures. The strongest association is a moderate correlation of -0.44 between present bias and patience. We find significant associations between the prosocial preference measures altruism, positive reciprocity, and trust as also reported by Falk et al. (2018). Most measures of pro-environmental behaviour are significantly and positively correlated, suggesting that they tap into the same underlying factor driving such behaviour. The strongest correlation is between SUM_Y and *GEN* with 0.54. The figure also shows that altruism is significantly and positively associated with all four measures of pro-environmental behaviour, and that strong positive reciprocity is associated with two pro-environmental measures. This suggests that the domain of social preferences is a strong contender for predicting pro-environmental behaviour in our pre-registered analysis. There are less systematic associations between the other preferences and pro-environmental behaviours (present bias is negatively associated only with *INV*; patience is significantly positively related only with *INV*; positive reciprocity shows a significant positive link only with *GEN*; and negative reciprocity is significantly positively associated only with SUM_Y).

Figure 4 Correlations between measures of economic preferences and pro-environmental behaviour. Bold font indicates significance at $p < 0.05$.



3.2. Predicting pro-environmental behaviour

Table 2 shows the results of our ceteris paribus analysis regarding the explanatory power of different economic preference. Altruism is a positive and highly significant predictor of the sum of pro-environmental behaviours enacted yesterday (Column 1; b = 1.428; p = 0.005). The results suggest that a participant whose altruism score is one standard deviation below the mean enacted 17.04 pro-environmental behaviours, and a participant whose altruism score is one standard deviation above the mean enacted 19.89 behaviours (holding all other variables constant at their mean). None of the other preference measures are significantly associated with the sum of pro-environmental behaviours enacted yesterday.

Neither altruism nor any other preference measure predicts the ratio of enacted pro-environmental behaviours yesterday over feasible behaviours (Column 2). This might suggest that participants with a higher altruism score are more likely to self-select into situations where pro-environmental behaviour is feasible. However, once altruists are in such situations, they are no more likely than non-altruists to act pro-environmentally.

Altruism does predict participants' general tendency to act pro-environmentally ($b = 0.097$; $p < 0.001$; Column 3). We predict that participants whose altruism score is one standard deviation below the mean report a score of 2.53 on the general pro-environmental behaviour measure. Participants whose altruism score is one standard deviation above the mean report a general pro-environmental behaviour score of 2.73. The association between altruism and the number of long-term investments in green products (Column 4) is not significant using our Bonferroni-adjusted p-value ($b = 0.243$; $p = 0.011$). These findings suggest that we can reject the null hypothesis of no associations between altruism and pro-environmental behaviour in everyday life and as measured using the general pro-environmental measure.

There is no evidence for problems of multicollinearity as the preference measures are at most moderately correlated with each other and the variance inflation factors for the linear regression models are low. However, an alternative analysis strategy would be to test for associations between the pro-environmental behaviour measures and each preference measure at a time. Tables S4.1 to S4.4 in the Supplementary Information present these analyses and show that our results hold when not controlling for any of the other preferences in the regressions. Similarly, the multi-level regressions reported in S5.1 confirm the results.

Table 2 Poisson regression models (Columns 1 and 4) and linear regression models (Columns 2 and 3) predicting four different pro-environmental behaviour measures by economic preferences and controls. Columns (1) and (4) present the average marginal effects.

	(1) *SUM*$_Y$	(2) *RTO*$_Y$	(3) *GEN*	(4) *INV*
Risk taking	0.143 (0.464)	0.004 (0.016)	0.024 (0.027)	0.112 (0.088)
Patience	0.121 (0.546)	0.024 (0.017)	0.020 (0.026)	0.025 (0.092)
Present bias	-0.251 (0.419)	0.014 (0.015)	0.005 (0.025)	-0.063 (0.106)
Pos. reciprocity	-0.228 (0.553)	0.008 (0.016)	0.057** (0.024)	0.186* (0.102)
Neg. reciprocity	0.791 (0.485)	0.011 (0.014)	-0.007 (0.022)	0.063 (0.087)
Altruism	1.428***† (0.506)	0.022 (0.015)	0.097***† (0.023)	0.243** (0.095)
Trust	0.532 (0.467)	0.013 (0.014)	-0.008 (0.022)	-0.061 (0.089)
Constant	 (0.161)	0.650*** (0.109)	2.507*** (0.160)	 (0.217)
Control variables	*Yes*	*Yes*	*Yes*	*Yes*
Observations	349	349	349	349
R-squared		0.094	0.235	

The control variables are age, gender, marital status, people living in household, education, income, math proficiency, and day of the week. Robust *SE* in parentheses. ***† $p < 0.007143$, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3.3. Principal component analysis

To better understand the associations between economic preferences and pro-environmental behaviours in our data, we conducted an exploratory principal component analysis. This analysis tested for clusters amongst the 20 pro-environmental behaviours that could have been enacted yesterday. One example of a potential cluster is transport choice: If individuals frequently take public transport, they might also be more likely to engage in another pro-environmental forms of transportation like walking or cycling. We then explored whether the economic preferences predict some clusters of behaviours but not others.

To conduct the principal component analysis, we first calculated how frequently participants enacted each of the 20 pro-environmental behaviours yesterday (with a minimum of 0 and a maximum of 3 as we measured 3 phases). We then performed the principal component analysis on the polychoric correlation matrix of the original set (Kolenikov & Angeles, 2005). The results of a Kaiser-Meyer-Olkin test indicate that a significant proportion of the variance in the original data was attributable to common variance, making the data suited to structure detection and data reduction via principal component analysis. We found four distinct components, accounting for 57% of variance in the data.[3] To aid the interpretation of these components, we used a Promax rotation and defined item loadings above 0.4 as contributing substantively to one of the four components. The resulting four components were the following:

- Eco-shopping behaviours: The highest loading behaviours all relate to shopping and result in reduced environmental impact. This includes the items "bought environmentally friendly products"; "bought products with less packing"; "used reusable bags when shopping".
- Energy and water saving: The highest loading behaviours are actions which result in reduced energy or water consumption and include "switched off electrical appliances"; "reduced heating"; "saved electricity in the house"; "conserved water when it was not directly needed".
- Awareness behaviours: The highest loading behaviours both relate to informing others or oneself about environmental issues: "talked to somebody about environmental issues"; "educated myself about the environment".
- Reducing consumption and waste: The highest loading behaviours all result in either lower levels of consumption or waste and include: "recycled"; "used a reusable cup/container for drinking"; "made a product instead of purchasing it".

Next, we created a new variable for each of the four components containing the predicted principal component scores for each individual across these four components and used ordinary least square regressions to test the predictive power of the seven social preference measures for each of the components (Table 3). The results indicate that altruism predicts eco-shopping behaviours ($b = 0.320$; $p = 0.011$), positive reciprocity predicts water and energy savings behaviours ($b = 0.237$; $p = 0.012$), and patience predicts awareness behaviours ($b = 0.163$;

[3] Components 1 and 2 have eigenvalues above two (5. 87 and 2.64 respectively). Components 3-6 have eigenvalues between 1 and 2 with the eigenvalues of all other components taking on values of less than 1. Examining the scree plot an elbow is apparent at Component 4, suggesting that 4 components should be retained and interpreted.

p = 0.040). Tables S6.2 to S6.5 confirm that these results are robust to including only one preference measure at a time in the regression model. Using the conservative Bonferroni-adjusted p-values would not yield any significant effect of economic preferences on the four clusters of pro-environmental behaviours. We interpret these results as suggestive evidence of the preference measures having differential effects on the different clusters of behaviours. Exploring these effects could therefore be a fruitful avenue of future research.

Table 3 Ordinary least squares regression models predicting principal component scores by the economic preference measures.

	(1) Eco-shopping behaviours	(2) Electricity and water saving behaviours	(3) Awareness behaviours	(4) Efforts to reduce consumption and waste
Risk taking	0.002 (0.105)	0.100 (0.096)	-0.137* (0.071)	0.044 (0.051)
Patience	0.001 (0.116)	-0.067 (0.100)	0.163** (0.079)	0.096* (0.052)
Present bias	-0.085 (0.091)	0.003 (0.097)	0.043 (0.071)	0.070 (0.046)
Pos. reciprocity	-0.088 (0.120)	0.237** (0.093)	0.075 (0.074)	0.027 (0.054)
Neg. reciprocity	0.190* (0.112)	-0.082 (0.088)	0.075 (0.075)	-0.051 (0.055)
Altruism	0.320** (0.125)	0.012 (0.088)	0.052 (0.068)	0.007 (0.051)
Trust	0.125 (0.108)	-0.104 (0.087)	-0.091 (0.074)	-0.015 (0.051)
Controls variables	*Yes*	*Yes*	*Yes*	*Yes*
Constant	2.840*** (0.617)	2.252*** (0.618)	0.137 (0.500)	-0.484 (0.312)
Observations	349	349	349	349
R-squared	0.138	0.124	0.107	0.109

The control variables are age, gender, marital status, people living in household, education, income, math proficiency, and day of the week. Robust *SE* in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4. Discussion

This paper presented a pre-registered test of whether seven economic preference measures (risk taking, patience, present bias, altruism, positive reciprocity, negative reciprocity, and trust) predict pro-environmental behaviours in everyday life. Our main result is that altruism is the only preference that is systematically associated with pro-environmental behaviour measured in everyday life, predicting the extent of engagement in pro-environmental behaviour as well as the general tendency to act pro-environmentally and past green investments. Moreover, we present evidence suggesting that the diverse range of everyday pro-environmental behaviours comprises at least four distinct clusters (eco-shopping behaviours, electricity and water savings, awareness behaviours, and consumption and waste reduction), and that these clusters are predicted by different economic preference measures.

Our results contribute to the growing literature exploring economic preferences as predictors of pro-environmental behaviour (e.g. Fuerst & Singh, 2018; He et al., 2019; Newell & Siikamäki, 2015; Schleich et al., 2019) by showing that altruism does not only predict a single pro-environmental behaviour but also summary measures containing several pro-environmental behaviours.[4] These pro-environmental behaviours contain at least four distinct clusters and we can speculate about why these are predicted by different preference measures. For example, eco-shopping behaviours tend to cost money, but efforts to reduce consumption and waste do not, which might help explaining why altruism predicts the former but not the latter. Similarly, awareness behaviours may impact the environment over long time horizons, which may help explaining why awareness behaviours are linked to patience. These speculations suggest that future research should focus more on theoretically relevant features of behaviours, such as their material costs, riskiness, and time horizons, rather than on whether the behaviours are pro-environmental or not.

We also contribute to the literature investigating the links between economic preferences and behaviours outside the lab more generally, sometimes referred to as external validity. A common result in these studies is that lab measures correlate at best weakly with field behaviours. For example, Galizzi & Navarro-Martinez (2018) find only very weak evidence for a correlation between social preferences as measures in the laboratory and field behaviours such as donating, helping others, and self-assesses past behaviour. Similarly, Delaney & Lades (2017) do not find evidence for a correlation between present bias and everyday self-control failures. Also Goeschl et al. (2020) find that behaviour in public good games generalises to

[4] A recent working paper by Fuhrmann, D'Exelle, & Verschoor (2020) also investigates the role of economic preferences for pro-environmental behaviour. While this working paper is the closest to our paper, there are several differences. For example, Fuhrmann et al. do not use the day reconstruction method but survey questions to measure a more limited number of pro-environmental behaviours, they investigate the topic as part of a field experiment in Peru, and they have not pre-registered the study. Their general result, that different preferences matter for different pro-environmental behaviours, however, is in line with our findings.

voluntary mitigation decisions only under certain circumstances. Studies focusing on potential explanations for the relatively low associations between preference measures and field behaviours have highlighted the importance of decision-making contexts (Schier, Ockenfels, & Hofmann, 2016) and compare self-reports to experimental measures as predictors of field behaviours (Gunten, Bartholow, & Martins, n.d.).

The null results we find for six of the seven preference measures suggest that not all preference domains are equally important in determining pro-environmental behaviour. For example, participants might not consider risk and time-related characteristics of pro-environmental behaviours when making the decisions. It might be the case that we need to revisit our theories linking economics preferences to pro-environmental behaviour. Another explanation for the lack of significant associations is that the economic preference measures might not be externally valid without taking contextual variables such as the preferences domain into account. One avenue for future research is to investigate the role of situational factors that explain when we do (and do not) expect to find significant correlations between preferences and pro-environmental behaviour. Another avenue is to investigate the predictive ability of domain-specific preferences in line with previous research suggesting that social preferences (Fleiß, Ackermann, Fleiß, Murphy, & Posch, 2019) risk preferences (Riddel, 2012), and time preferences (Augenblick, Niederle, & Sprenger, 2015) differ depending on the domain in which they are measured.

The paper also contributes to the literature on the determinants of pro-environmental behaviour. This literature has identified a broad range of factors explaining why some people behave more pro-environmentally than others, including green identity (Akerlof & Kranton, 2000; Binder & Blankenberg, 2017; Whitmarsh & O'Neill, 2010), social norms (Farrow, Grolleau, & Ibanez, 2017), sense of control (Gifford & Nilsson, 2014), and personality traits (Markowitz, Goldberg, Ashton, & Lee, 2012).We add to this literature by showing that altruism, but none of the other economic preferences we measured, might explain some of the variance that the other studies have not accounted for.

We also contribute to the literature on measuring pro-environmental behaviour (Melo, Ge, Craig, Brewer, & Thronicker, 2018; Schmitt et al., 2018; Whitmarsh & O'Neill, 2010). While most previous research focuses on general tendencies to behave pro-environmentally, we show that it is possible to quantify pro-environmental behaviour in everyday life using the day reconstruction method. This approach allows us to gain insights into people's everyday lives where many environmentally-relevant behaviours are driven more by automatic processes and habits and less by cognitive deliberation (Kahneman, 2011). Our exploratory analysis highlights several distinct clusters of pro-environmental behaviours that might differ in the underlying processes driving the behaviours. This suggests that simply aggregating structurally different behaviours might hide their underlying differences. Systematically identifying specific behaviours that are structurally similar (e.g., in terms of incurring material costs or having a time-component with costs incurred now and environmental benefits later in the future) seems a crucial exercise in understanding pro-environmental behaviour.

Finally, we suggest that there are difficulties when using the RTO_{Y} measure – a common approach in existing literature (Binder & Blankenberg, 2017; Bissing-Olson et al., 2016). It does not adequately differentiate participants who enact many pro-environmental behaviours from participants who enact only few pro-environmental behaviours. For example, a participant who enacts 20 out of 20 feasible behaviours gets the same score as a participant who enacts 1 out of 1 feasible behaviour. Additionally, the measure is likely to overestimate the extent of conscious pro-environmental actions, because some participants reporting "yes" for a specific behaviour might not have had a choice of whether to engage in this pro-environmental action.

Limitations of this paper include the lack of a nationally representative sample and the novel and not yet validated use of the day reconstruction method as a tool to measure pro-environmental behaviour in everyday life. A recent paper comparing data from the day reconstruction method with data from the experience sampling method shows that agreement between both methods is not always high and that expectations might influence answers people give in day reconstruction studies (Lucas, Wallsworth, Anusic, & Donnellan, 2020).

Finally, our results have some potential implications for future research that aims to inform policy. Our main finding suggests that campaigns that aim to encourage pro-environmental behaviours should focus on testing messages that highlight the altruistic character of these behaviours. And the structural differences in the various pro-environmental behaviours we find in the principal component analysis suggests that there is no one-size-fits-all solution inspired by economic preference measures. Identifying clusters of similar behaviours and targeting these clusters through targeted interventions seems vital in this endeavour.

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Supplementary information for:

Do economic preferences predict pro-environmental behaviours?

(for online publication only)

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Contents:

S1. Descriptive Statistics

Table S1.1 Descriptive statistics.

Variable	*N*	Mean	*SD*	Min	Max
Preference measures					
Risk taking	349	0	1	-2.27	3.72
Patience	349	0	1	-2.07	1.99
Present Bias	349	0	1	-3.04	4.4
Positive reciprocity	349	0	1	-3.5	1.72
Negative reciprocity	349	0	1	-1.84	2.69
Altruism	349	0	1	-2.54	2.81
Trust	349	0	1	-2.06	2.01
Math score	349	0	1	-2.05	1.52
Everyday pro-environmental behaviours					
Saved electricity in the house	349	2.25	1.01	0	3
Switched off electrical appliances	349	1.95	1.09	0	3
Used a reusable cup/container for drinking	349	1.81	1.23	0	3
Recycled	349	1.77	1.05	0	3
Conserved water when it was not directly needed	349	1.64	1.26	0	3
Walked or cycled for more than 5 minutes	349	1.41	1.08	0	3
Reduced heating	349	1.32	1.29	0	3
I ate vegetarian/vegan food	349	0.85	1.12	0	3
Used reusable bags when shopping	349	0.84	0.92	0	3
Used both sides of the paper when drawing or printing	349	0.72	1.05	0	3
Made/produced a product myself	349	0.68	0.97	0	3
Reused or repaired items	349	0.66	0.95	0	3
Used reusable hygiene products	349	0.59	1.01	0	3
Used public transport	349	0.41	0.85	0	3
Bought seasonal, organic, and/or local food	349	0.4	0.74	0	3
Bought products with less packaging	349	0.29	0.63	0	3
Talked to somebody about environmental issues	349	0.27	0.67	0	3
Educated myself about the environment	349	0.21	0.61	0	3
Car-pooled	349	0.21	0.60	0	3
Bought environmentally-friendly products	349	0.20	0.55	0	3
General pro-environmental behaviours					
GEN	349	2.63	0.41	1.14	3.68
INV	349	2.87	1.69	0	8
Socio-economic control variables					
Age	349	37.03	12.90	18	72
Female	349	0.63	.48	0	1
People in household	349	2.93	1.36	1	8

Table S1.2 Descriptive statistics.

Variable	*N*	%
More socio-economic control variables		
Marital status	349	100
Single	124	35.53
Married / cohabiting	191	54.73
Other	34	9.74
Education	349	100
Leaving Cert or less	29	8.31
Leaving Certificate/Diploma	23	6.59
Some college/No degree	59	16.91
College graduate	40	11.46
Bachelor's degree	123	35.24
Masters	52	14.9
Other	23	6.59
Income	349	100
£0 - £100	31	8.88
£101 - £600	37	10.6
£601 - £1 000	38	10.89
£1 001 - £2 000	111	31.81
£2 001 - £5 000	62	17.77
£5 001 or more	39	11.17
Rather not say	31	8.88

Figure S1.1 Answers to the question "Please indicate how often you take each action" used to calculate *GEN*.

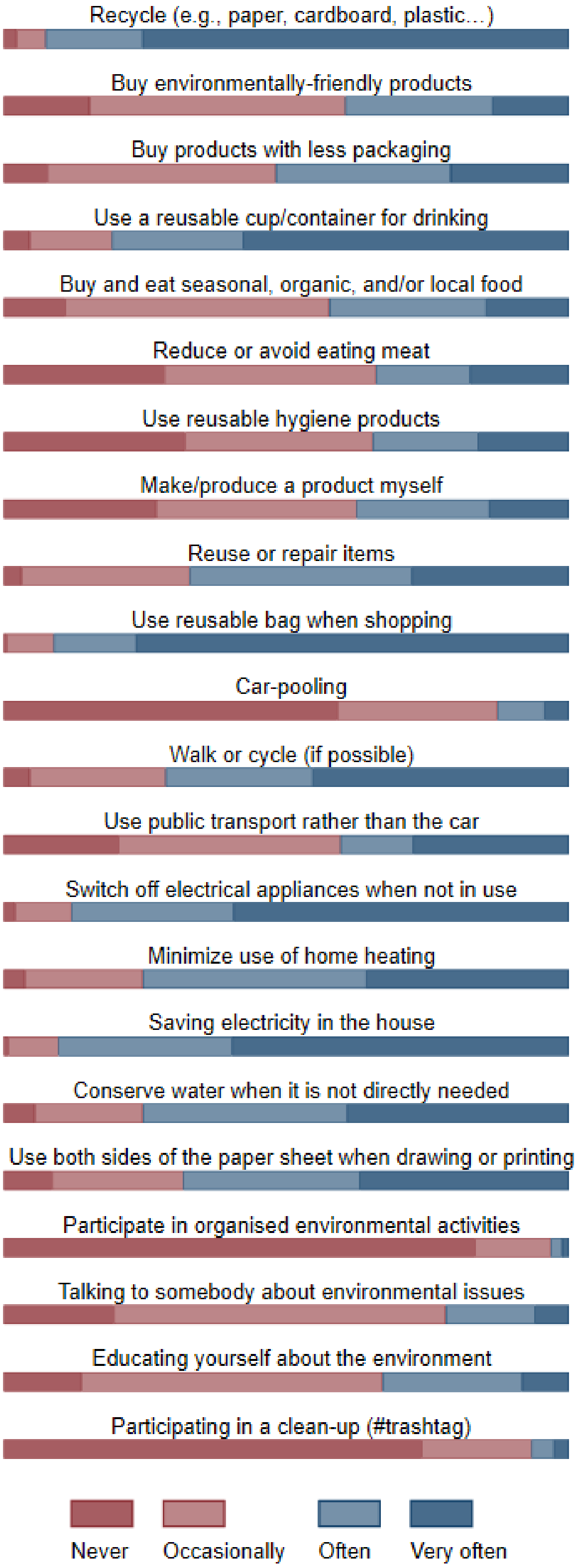
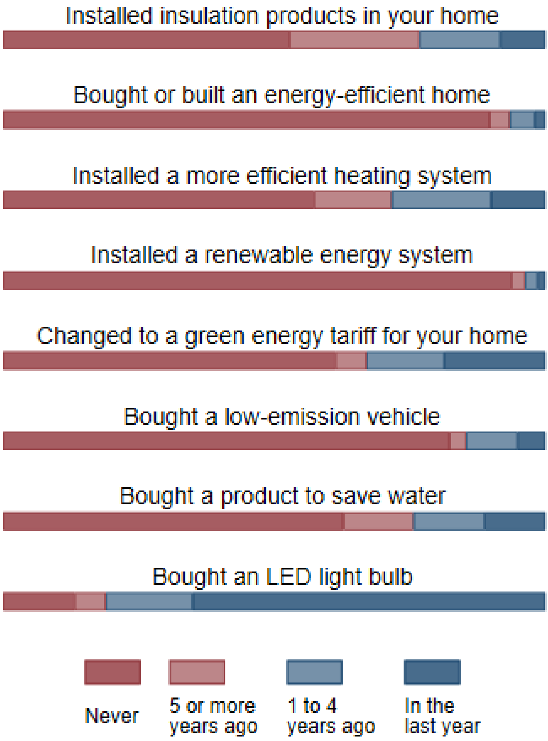


Figure S1.2 Answers to the question "Please indicate the last time you took this action (if at all)" used to calculate *INV*.



S2. Economic preference measures

Risk taking: We measured risk preferences using a series of five interdependent hypothetical binary choices of the form "What would you prefer: A 50 percent chance to win £300 when at the same time there is 50 percent chance to win nothing? Or: The amount of £X as a sure payment?", where the X was different in each question. If participants chose the sure payment, the next sure payment would be lower. If participants chose the lottery, the next sure payment would be higher. This staircase method of asking the five questions leads to 32 possible ordered outcomes. Additionally, we asked participants to answer the question "In general, how willing are you to take risks?" on an 11-point Likert scale from "0 = Completely unwilling to do so" to "10 = Very willing to do so".

Patience: We measured patience using a series of five interdependent hypothetical binary choices of the form "*Would you rather receive £100 today or $X in 12 months?*", where *X* was different in each question. If participants chose to be paid today, the next delayed payment would be higher. If participants chose to be paid after 12 months, the next delayed payment would be lower. Again, this allows for 32 potential ordered outcomes. Additionally, we asked participants to answer the question "*How willing are you to give up something that is beneficial for you today in order to benefit more from that in the future?*" on an 11-point Likert scale from "*0 = Completely unwilling to do so*" to "*10 = Very willing to do so*".

Present bias: We measured present bias by repeated the quantitative time preference questions, but changing the dates. Rather than having to choose between today and in 12 months, participants had to choose between in 12 months and in 24 months. We calculated the difference between both time preference measures as our indicator for present bias. For example, if participants obtained a patience measure of 28 in the today-versus-in-12-months question, and a patience measure of 30 in the in-12-months-versus-in-24-months question, present bias would be calculated as 2. Additionally, we asked participants to indicate whether they agreed with the statement "*I tend to postpone tasks even if I know it would be better to do them right away*" on a Likert-scale from "*0 = Does not describe me at all*" to "*10 = Describes me perfectly*". Since Falk et al. (2018) do not provide a weighting for these questions, we use the same weighting as for the patience measure.

Positive reciprocity: We measured positive reciprocity by asking participants to imagine that they were lost and that a stranger offered to take them to their destination for a personal cost of £30. Respondents were then asked whether they would give one out of several presents (worth between £5 and £30 euros) to the stranger as a "thank you." Additionally, we asked participants to indicate whether they agreed with the statement "*When someone does me a favour, I am willing to return it"* on a 11-point Likert scale from "*0 = Does not describe me at all"* to "*10 = Describes me perfectly"*.

Negative reciprocity: We measured negative reciprocity by asking participants about the extent to which the statement "*If I am treated very unjustly, I will take revenge at the first occasion, even if there is a cost to do so"* described them on an 11-point Likert scale from "*0 = Does not describe me at all"* to "*10 = Describes me perfectly"* and the *two* questions "*How willing or unwilling are you to punish someone who treats you (*in the second question: *others) unfairly, even if there may be costs for you?"* on 11-point Likert scales from "*0 = Completely unwilling to do so"* to "*10 = Very willing to do so".*

Altruism: We measured altruism by asking participants "Imagine the following situation: Today you unexpectedly received £1000. How much of this amount in £ would you donate to a good cause?" and the question "How willing or unwilling are you to give to good causes without expecting anything in return?” to be answered on an 11-point Likert scale from “0 = Completely unwilling to do so” to “10 = Very willing to do so.”

Trust: We measured trust by asking participants to what extent they agreed with the statement “*I assume that people have only the best intentions”* on a, 11-point Likert scale from “*0 = Does not describe me at all”* to “*10 = Describes me perfectly.*”

Table S2.1 Economic preference measures and the weights used following Falk et al. (2016).

Preference	*Item*	*Weight*
Risk taking	Lottery choice sequence using staircase method	0.473
	Self-assessment: willingness to take risks in general	0.527
Patience	Intertemporal choice sequence using staircase method	0.712
	Self-assessment: willingness to wait	0.288
Present bias	Intertemporal choice sequence using staircase method	0.712
	Self-assessment: willingness to procrastinate	0.288
Positive reciprocity	Gift in exchange for help	0.515
	Self-assessment: willingness to return a favour	0.485
Negative reciprocity	Self-assessment: willingness to take revenge	0.374
	Self-assessment: willingness to punish unfair behaviour toward self	0.313
	Self-assessment: willingness to punish unfair behaviour toward others	0.313
Altruism	Donation decision	0.635
	Self-assessment: willingness to give to good causes	0.365
Trust	Self-assessment: people have only the best intentions	1

S3 Measures elicited in the survey but not used in manuscript

For each part of the day (morning, afternoon, and evening), we asked participants to indicate whether they engaged in a list of further activities (such as “*Commuting to work/uni*”, “*Working/studying*”, and “*Eating*”), where they were (“*At home*”, “*At work/school/uni*”, and “*Somewhere else*”), and whether they were enacting with anybody (such as “*Spouse/significant other*”, “*Children*”, and “*Nobody*”). The most frequent activities were “*Eating*”, “W*atching TV*”, “*Resting/relaxing*”, and “*Surfing on the internet*”. We also asked whether participants were at home, at work/school/university, or somewhere else and who they had social interactions with during their parts of the day. We also asked participants whether each of the three parts of yesterday was a normal on a scale from “*0 = Totally normal*” to “*6 = Not normal at all*” (M=3.53; SD=2.04).

We also measured green identity asking participants to indicate the degree to which they agree with statements such as "*I think of myself as someone who is very concerned with environmental issues*", "*I consider myself as an environmentally aware consumer*", and "*I would be embarrassed to be seen as having an environmentally friendly lifestyle*" on a scale from "*0 = Totally disagree*" to "*6 = Completely agree*", following Whitmarsh & O'Neill (2010). Finally, we measured trait self-control using the 13-item Brief Self-Control Scale (Tangney et al., 2004), life satisfaction using the Satisfaction With Life Scale (Diener, Emmons, Larsen, & Griffin, 1985), and in the DRM we asked participants how they felt.

S4 Predicting pro-environmental behaviours by each preference measure independently.

Table S4.1 Poisson regression models predicting the sum of pro-environmental behaviours yesterday by economic preferences and controls. Presenting average marginal effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	SUM_Y	SUM_Y	SUM_Y	SUM_Y	SUM_Y	SUM_Y	SUM_Y
Risk taking	0.482						
	(0.464)						
Patience		0.237					
		(0.512)					
Present bias			-0.322				
			(0.388)				
Pos. reciprocity				0.376			
				(0.526)			
Neg. reciprocity					0.709		
					(0.480)		
Altruism						1.500***†	
						(0.490)	
Trust							0.693
							(0.443)
Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	349	349	349	349	349	349	349

The control variables are age, gender, marital status, people living in household, education, income, math proficiency, and day of the week. Robust *SE* in parentheses. ***†p<0.007143, ***p<0.01, **p<0.05, *p<0.1.

Table S4.2 Linear regression models predicting the ratio of the sum of pro-environmental behaviours over the feasible behaviours yesterday by economic preferences and controls.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	RTO_Y	RTO_Y	RTO_Y	RTO_Y	RTO_Y	RTO_Y	RTO_Y
Risk taking	0.011						
	(0.016)						
Patience		0.020					
		(0.015)					
Present bias			0.004				
			(0.014)				
Pos. reciprocity				0.022			
				(0.015)			
Neg. reciprocity					0.009		
					(0.013)		
Altruism						0.029**	
						(0.015)	
Trust							0.020
							(0.013)
Constant	0.617***	0.620***	0.621***	0.647***	0.625***	0.647***	0.632***
	(0.107)	(0.105)	(0.105)	(0.105)	(0.106)	(0.106)	(0.104)
Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	349	349	349	349	349	349	349
R-squared	0.070	0.075	0.069	0.076	0.070	0.081	0.075

The control variables are age, gender, marital status, people living in household, education, income, math proficiency, and day of the week. Robust *SE* in parentheses. ***†p<0.007143, ***p<0.01, **p<0.05, *p<0.1.

Table S4.3 Linear regression models predicting the general pro-environmental behaviour measure by economic preferences and controls.

VARIABLES	(1) *GEN*	(2) *GEN*	(3) *GEN*	(4) *GEN*	(5) *GEN*	(6) *GEN*	(7) *GEN*
Risk taking	0.039						
	(0.028)						
Patience		0.029					
		(0.023)					
Present bias			-0.006				
			(0.022)				
Pos. reciprocity				0.091***†			
				(0.023)			
Neg. reciprocity					-0.001		
					(0.022)		
Altruism						0.116***†	
						(0.021)	
Trust							0.031
							(0.021)
Constant	2.364***	2.381***	2.387***	2.486***	2.384***	2.484***	2.400***
	(0.167)	(0.169)	(0.168)	(0.163)	(0.170)	(0.163)	(0.168)
Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	349	349	349	349	349	349	349
R-squared	0.152	0.149	0.145	0.187	0.145	0.214	0.150

The control variables are age, gender, marital status, people living in household, education, income, math proficiency, and day of the week. Robust *SE* in parentheses. ***†p<0.007143, ***p<0.01, **p<0.05, *p<0.1.

Table S4.4 Poisson regression models predicting the number of green investments by economic preferences and controls. Presenting average marginal effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	INV	INV	INV	INV	INV	INV	IN\V
Risk taking	0.162*						
	(0.088)						
Patience		0.073					
		(0.081)					
Present bias			-0.079				
			(0.093)				
Pos. reciprocity				0.258***			
				(0.099)			
Neg. reciprocity					0.082		
					(0.087)		
Altruism						0.297***†	
						(0.094)	
Trust							0.038
							(0.091)
Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	349	349	349	349	349	349	349

The control variables are age, gender, marital status, people living in household, education, income, math proficiency, and day of the week. Robust *SE* in parentheses. ***†p<0.007143, ***p<0.01, **p<0.05, *p<0.1.

S5 Multi-level analysis

Table S5.1 Multi-level poisson regression models (Columns 1 and 2) and multi-level linear regression models (Columns 3 and 4) predicting four pro-environmental behaviours yesterday by economic preferences and controls.

VARIABLES	(1) SUM_YP	(2) SUM_YP	(3) RTO_YP	(4) RTO_YP
Risk taking	0.011	0.018	0.006	0.004
	(0.028)	(0.026)	(0.015)	(0.016)
Patience	0.012	0.012	0.020	0.022
	(0.031)	(0.030)	(0.016)	(0.016)
Present bias	-0.015	-0.010	0.011	0.013
	(0.024)	(0.022)	(0.014)	(0.014)
Pos. reciprocity	0.002	0.002	0.007	0.009
	(0.030)	(0.027)	(0.015)	(0.015)
Neg. reciprocity	0.038	0.031	0.010	0.010
	(0.026)	(0.026)	(0.013)	(0.013)
Altruism	0.083***	0.072***	0.021	0.019
	(0.028)	(0.027)	(0.014)	(0.014)
Trust	0.021	0.029	0.013	0.015
	(0.025)	(0.024)	(0.013)	(0.013)
Phase controls	*No*	*Yes*	*No*	*Yes*
Constant	1.553***	1.513***	0.667***	0.688***
	(0.174)	(0.186)	(0.103)	(0.108)
Observations	1,047	1,047	1,034	1,034
Number of groups	349	349	349	349

The control variables are age, gender, marital status, people living in household, education, income, math proficiency, and day of the week. The Phase control variables are dummies for the activities, locations, and social interactions. Robust *SE* in parentheses. ***p<0.01, **p<0.05, *p<0.1.

S6 Principal component analysis

Table S6.1 Principal component analysis using 20 pro-environmental behaviours yesterday.

	C1	C2	C3	C4
Recycled	0.134	0.019	-0.055	**0.419**
Bought environmentally-friendly products	**0.406**	-0.053	0.101	0.073
Bought products with less packaging	**0.549**	0.007	-0.110	0.034
Used a reusable cup/container for drinking	0.052	-0.038	-0.019	**0.457**
Bought seasonal, organic, and/or local food	0.395	-0.028	0.041	0.086
Ate vegetarian/vegan food	-0.183	-0.003	0.328	0.167
Used reusable hygiene products	0.082	-0.040	0.156	0.313
Made/produced a product myself	-0.013	-0.025	0.040	**0.424**
Reused or repaired items	-0.051	0.019	0.223	0.288
Used reusable bags when shopping	**0.468**	0.098	-0.101	-0.008
Car-pooled	0.019	0.018	0.314	-0.339
Walked or cycled for more than 5 minutes	0.250	0.015	0.088	-0.073
Used public transport	0.158	-0.119	0.299	-0.295
Switched off electrical appliances	-0.031	**0.436**	-0.006	0.015
Reduced heating	0.023	**0.436**	0.099	-0.092
Saved electricity in the house	0.010	**0.562**	-0.034	-0.019
Conserved water when it was not directly needed	0.040	**0.459**	-0.020	0.046
Used both sides of the paper when drawing or printing	0.054	0.239	0.137	0.037
Talked to someone about environmental issues	-0.117	0.057	**0.537**	-0.001
Educated myself about the environment	0.013	-0.042	**0.524**	-0.030

Figure S6.1 Screeplot of eigenvalues after principal component analysis

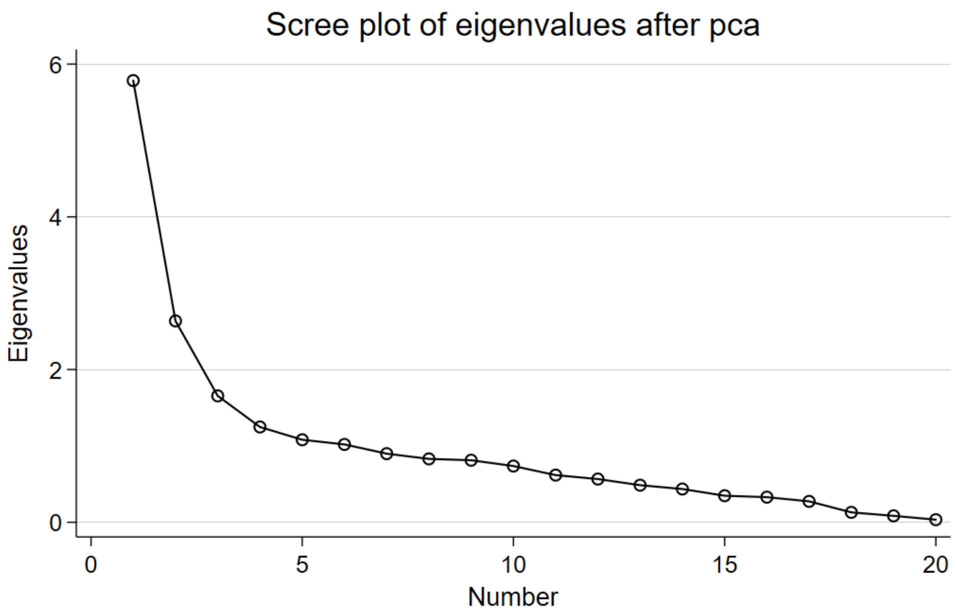


Table S6.2 Economic preference measures predicting the principal component scores of 'eco-shopping behaviours.'

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Risk taking	0.080						
	(0.105)						
Patience		0.035					
		(0.109)					
Present bias			-0.083				
			(0.084)				
Pos. reciprocity				0.044			
				(0.112)			
Neg. reciprocity					0.167		
					(0.109)		
Altruism						0.324***	
						(0.116)	
Trust							0.147
							(0.099)
Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Constant	2.465***	2.504***	2.542***	2.558***	2.565***	2.784***	2.580***
	(0.606)	(0.606)	(0.603)	(0.619)	(0.595)	(0.589)	(0.613)
N	349	349	349	349	349	349	349
R^2	0.097	0.096	0.098	0.096	0.103	0.124	0.102

OLS estimates with robust *SE* in parentheses. The control variables are age, gender, marital status, people living in household, education, income, math proficiency, and day of the week. ***p<0.01, **p<0.05, *p<0.1.

Table S6.3 Economic preference measures predicting the principal component scores of ‘energy and water saving behaviours.’

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Risk taking	0.097						
	(0.095)						
Patience		-0.038					
		(0.092)					
Present bias			0.027				
			(0.088)				
Pos. reciprocity				0.216**			
				(0.088)			
Neg. reciprocity					-0.041		
					(0.086)		
Altruism						0.071	
						(0.083)	
Trust							-0.032
							(0.085)
Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Constant	2.050***	2.107***	2.092***	2.344***	2.089***	2.163***	2.087***
	(0.607)	(0.603)	(0.605)	(0.598)	(0.604)	(0.612)	(0.607)
N	349	349	349	349	349	349	349
R^2	0.101	0.099	0.099	0.115	0.099	0.100	0.099

OLS estimates with robust *SE* in parentheses. The control variables are age, gender, marital status, people living in household, education, income, math proficiency, and day of the week. ***p<0.01, **p<0.05, *p<0.1.

Table S6.4 Economic preference measures predicting the principal component scores of 'awareness behaviours.'

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Risk taking	-0.122*						
	(0.067)						
Patience		0.137*					
		(0.072)					
Present bias			-0.005				
			(0.063)				
Pos. reciprocity				0.082			
				(0.071)			
Neg. reciprocity					0.063		
					(0.074)		
Altruism						0.049	
						(0.066)	
Trust							-0.079
							(0.072)
Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Constant	0.058	-0.025	-0.007	0.083	0.013	0.033	-0.047
	(0.490)	(0.492)	(0.489)	(0.494)	(0.493)	(0.494)	(0.493)
N	349	349	349	349	349	349	349
R^2	0.083	0.086	0.076	0.079	0.078	0.077	0.079

OLS estimates with robust *SE* in parentheses. The control variables are age, gender, marital status, people living in household, education, income, math proficiency, and day of the week. ***p<0.01, **p<0.05, *p<0.1.

Table S6.5 Economic preference measures predicting the principal component scores of 'efforts to reduce consumption and waste.'

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Risk taking	0.035						
	(0.049)						
Patience		0.073					
		(0.045)					
Present bias			0.024				
			(0.038)				
Pos. reciprocity				0.043			
				(0.050)			
Neg. reciprocity					-0.044		
					(0.052)		
Altruism						0.018	
						(0.047)	
Trust							0.011
							(0.046)
Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Constant	-0.451	-0.441	-0.442	-0.385	-0.447	-0.417	-0.427
	(0.289)	(0.298)	(0.292)	(0.302)	(0.295)	(0.293)	(0.295)
N	349	349	349	349	349	349	349
R^2	0.094	0.099	0.093	0.095	0.095	0.093	0.093

OLS estimates with robust *SE* in parentheses. The control variables are age, gender, marital status, people living in household, education, income, math proficiency, and day of the week. ***p<0.01, **p<0.05, *p<0.1.