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Analysis

Do economic preferences predict pro-environmental behaviour?

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ABSTRACT

Understanding the determinants of pro-environmental behaviour is key to addressing many environmental challenges. Economic theory and empirical evidence suggest that human behaviour is partly determined by people's economic preferences which therefore should predict individual differences in pro-environmental behaviour. In a pre-registered study, we elicit seven preference measures (risk taking, patience, present bias, altruism, positive reciprocity, negative reciprocity, and trust) and test whether they 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 pro-social aspects of everyday pro-environmental behaviour are more salient to people than the riskiness and intertemporal structure of these behaviours. 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.

1. Introduction

Human activity is a key driver of many of the environmental challenges that the world currently faces, including biodiversity loss, water and air pollution, and climate change. As a result, researchers, practitioners, and policymakers alike have highlighted behavioural change as a central component of strategies aimed at addressing these challenges. Of particular importance is the encouragement of pro-environmental behaviours in people's everyday lives (Hoegh-Guldberg et al., 2018; Ockwell et al., 2009; OECD, 2017; Stern, 2007). Pro-environmental behaviours are those actions that avoid environmental 'bads', such as CO_2 emissions or plastic pollution (Steg and Vlek, 2009). Examples include conserving water and electricity, recycling, choosing sustainable transport options, and avoiding food items with large environmental footprints.

Designing policies that effectively encourage pro-environmental behaviour requires an understanding of the determinants of this behaviour. One way to identify determinants of pro-environmental behaviour is to find out why some people act environmentally friendly while others do not, that is to analyse inter-individual differences. Economics and other social sciences assume that individual differences in people's tendencies to take risks, delay outcomes, and act pro-socially—often referred to as economic preferences—can explain why people behave differently (e.g., DellaVigna, 2018). The present paper therefore tests whether seven individual preference measures (risk taking, patience, present bias, altruism, positive reciprocity, negative reciprocity, and trust) predict pro-environmental behaviour in everyday life.

Empirical evidence shows that the individual preference measures predict a wide range of behaviours. Risk taking is associated with investment decisions, labour outcomes, and health outcomes (Anderson and Mellor, 2008; Bonin et al., 2007; Dohmen et al., 2011). Patience and present bias are linked to borrowing and creditworthiness (Meier and Sprenger, 2010, 2012). Altruism, positive reciprocity, negative reciprocity, and trust predict charitable giving, labour market outcomes, and subjective wellbeing (DellaVigna et al., 2012; Dohmen et al., 2009). Despite these findings, there is an ongoing discussion regarding the predictive power of economic preferences and their importance relative to other individual characteristics, contextual, and situational factors (Charness et al., 2020; Cohen et al., 2021; Galizzi and Navarro-Martinez, 2018; Goeschl et al., 2020; Levitt and List, 2007; Mata et al., 2018).

There are good reasons to expect that the individual preference measures will also predict pro-environmental behaviours. Pro-environmental behaviours typically generate uncertain benefits, suggesting links to risk

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preferences. Indeed, risk taking is positively associated with the likelihood of investing in energy efficient technologies (He et al., 2019; Qiu et al., 2014). Pro-environmental behaviours are usually costly in the present and beneficial in the future, hinting at the importance of time preferences. This is supported by studies reporting that patience and present bias predict investments in energy efficient technologies (Fuerst and Singh, 2018; Newell and Siikamäki, 2015). Pro-environmental behaviours also impose positive externalities on others, which implies links to social preferences (Handgraaf et al., 2017). Altruism and positive reciprocity have been linked to higher adoption of green electricity programmes and higher donations to a national park (Alpizar et al., 2008; Clark et al., 2003; Kotchen and Moore, 2007), and trust has been positively associated with pro-environmental behaviours (Tam and Chan, 2018). We are not aware of previous work linking negative reciprocity to pro-environmental behaviour, but its importance in predicting behavioural outcomes in other domains, such as labour market and life outcomes, highlights its relevance (e.g., Dohmen et al., 2009).

Importantly, the existing literature examining the links between individual preferences and pro-environmental behaviours also documents null results and, in some cases, contradictory results (Bradford et al., 2017; Goeschl et al., 2020; Paladino, 2005; Schleich et al., 2019), suggesting that a more systematic investigation is needed.

Several reasons could potentially explain the contradictory results in the literature. First, recent research on the links between individual preferences and pro-environmental behaviour tends to focus on a single pro-environmental behaviour as predicted by a single preference measure. 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 multiple preferences simultaneously, and therefore studies that focus on a single preference measure without controlling for others may misrepresent the true relationship. For example, the future is uncertain (Andersen et al., 2008), and short-term temptations to be selfish may conflict with better judgments to act pro-socially (Martinsson et al., 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. Together these behaviours can have large environmental consequences as their impacts accrue over time.

To overcome these limitations, the present paper presents a systematic, pre-registered test of whether the seven individual preference measures predict various pro-environmental behaviours enacted in people's everyday lives. We construct several indices measuring the extent and intensity of pro-environmental behaviour. Using these aggregate indices avoids identifying correlations driven by the riskiness, timing, or social elements of single pro-environmental behaviours. We conduct ceteris-paribus analyses predicting pro-environmental behaviours by all seven preference measures simultaneously to identify the effect of a single preference measure while controlling for others. Finally, we measure 20 different 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 us to identify clusters of structurally similar pro-environmental behaviours.

Participants in our online survey ($N = 349$) first completed the seven individual preference measures (risk taking, patience, present bias, positive reciprocity, negative reciprocity, altruism, and trust) using experimentally validated survey items designed to predict choices in incentivised experiments (Falk et al., 2018; Falk et al., 2016). Participants then reconstructed their previous day using a technique that facilitates recall from people's episodic memory (the day reconstruction method as developed by Kahneman et al., 2004) and reported the pro-environmental behaviours they engaged in yesterday. We 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. This measure reflects that not every participant had the same number of opportunities to engage in pro-environmental behaviour and 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 past 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 Component Analysis (PCA) 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 preference measures 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 preferences. It is worth further considering the structural differences in decision making across different 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 further investigate the role of individual and situational factors, including the domain-specificity of preference measures. Lastly, the study also contributes to the literature on measuring pro-environmental behaviour (e.g., Lange and Dewitte, 2019) by providing a measure of high-frequency everyday behaviours while reducing recall bias.

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 United Kingdom, 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% were female, 36% were single and 55% married or cohabiting, 43% had at least a college degree, 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 of 0 to 10. Table S1.1 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 included questions on participants' general engagement in pro-environmental behaviours, their past green investments, psychological survey measures, and their socio-economic background. All participants completed the measures in the same order. Sections S2 and S3 in the Supplementary Information summarise all the variables we measured and Section S7 presents the survey materials.

2.2. Economic Preference Measures

We measured participants' risk taking, patience, present bias, positive reciprocity, negative reciprocity, altruism, and trust following Falk et al. (2018). Their approach combines quantitative and qualitative survey questions for each preference type designed to predict behaviour in incentivised choice experiments. For example, the risk taking measure combines a hypothetical lottery choice sequence, where people choose five times between a safe and a risky but potentially higher-paying option, with a self-assessment about the willingness to take risks in general. We first computed the z-scores of the two 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 and Agyeman, 2002). We present the detailed description of the survey items to measure preferences 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. The day reconstruction method is frequently used to provide detailed information on participants' lives "yesterday", i.e. one day prior to the day of the study. 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 these phases. This first step is essential to help participants retrieve information from their episodic memory. In a second step, we showed participants their diary entries again and asked them to answer specific follow-up questions for each of the three phases. Since 349 participants took part in this study, we obtained 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 (Fig. 1 in Section 3.1 lists all 20 behaviours). The answer options were "*Yes*", "*No, but I could have*", and "*Not applicable or can't recall*". To select the pro-environmental behaviours, we first created a list of behaviours used in recent papers which follow an impact-oriented approach, i.e. they examine behaviours that affect the natural environment. We drew measures from work which had previously used naturalistic monitoring tools to assess a range of pro-environmental behaviours in everyday life and which is, therefore, of direct relevance to the current work (Bissing-Olson et al., 2016). We complemented these measures with others from three papers which explore the determinants of pro-environmental behaviour using self-reported measures (Blankenberg and Alhusen, 2018; Schmitt et al., 2018; Whitmarsh and O'Neill, 2010), adding behaviours that do not appear in Bissing-Olson et al. (2016) and which can be considered impactful pro-environmental behaviours. To avoid attrition, we restricted the questionnaire to 20 behaviours, picking behaviours that are typically enacted in everyday life while avoiding overlap.

Our first summary measure of everyday pro-environmental behaviour is the sum of pro-environmental behaviours that participants had enacted yesterday (SUM_Y). Since we asked about 20 behaviours in each of the three phases (morning, afternoon, and evening), this summary 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 and 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 instruments (Lades et al., 2019). The method allowed us to measure pro-environmental behaviours as enacted in everyday life with minimal recall bias. It aims to elicit people's behaviours and experiences as retrieved from their episodic memory, which stores memories of everyday events, rather than their semantic memory, which stores facts, ideas, and concepts (Tulving, 1972). To make sure participants answer the survey questions using their episodic memory, day reconstruction studies tend to focus on "yesterday" rather than longer periods such as "last week," which would make it more difficult for people to re-live what they have done and how they have felt in the same level of detail. The day reconstruction method has been used extensively in economic and psychological research (Daly et al., 2014; Delaney and Lades, 2017; Diener and Tay, 2014; Doyle et al., 2017; Knabe et al., 2010). It provides data comparable to other experience sampling methods, but places a lower burden on participants (Dockray et al., 2010; Kim et al., 2013; Sonnenberg et al., 2012).[1]

Additionally, 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 of 1 ("*Never*") to 4 ("*Very often*"), and we calculated the average of these answers (see Table S1.1 and Fig. S1.1 in the Supplementary Information). 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 total number of investments (see Table S1.1 and Fig. S1.2).

2.4. Analysis Strategy

We pre-registered seven directional research hypotheses on the associations between preference measures and pro-environmental behaviours. We predicted that higher levels of risk taking and present bias would be asso-

[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 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 et al. (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.

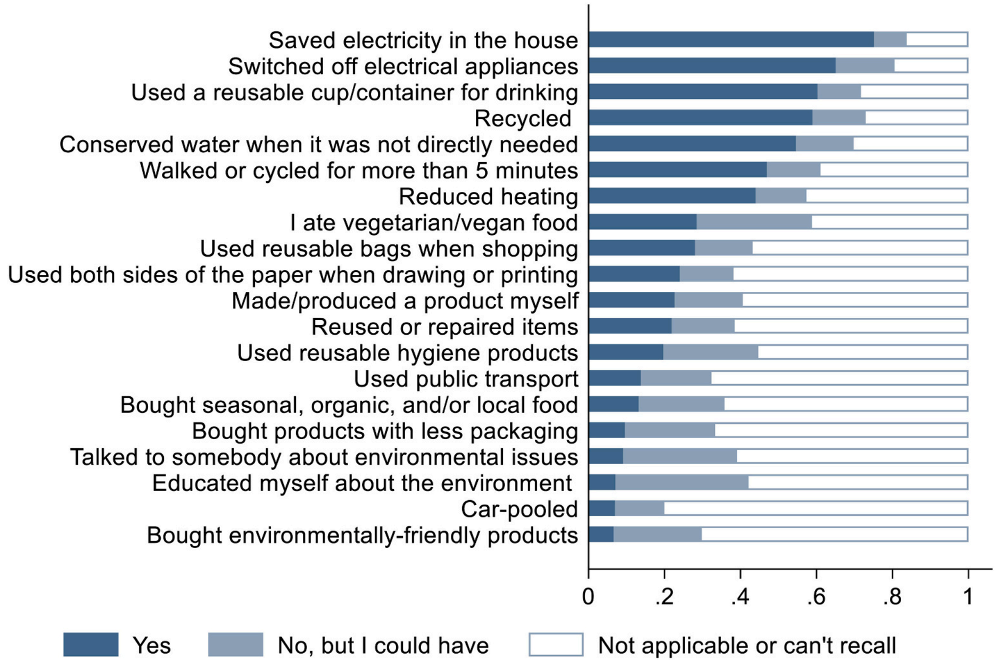

Fig. 1. Frequency of enacting everyday pro-environmental behaviours.

ciated 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*, and *INV*) for individual *i*. The independent variables include the seven standardised preference measures as suggested by their names. The vector $\boldsymbol{X}_i$ represents the control variables age, gender, relationship status, household size, income, self-reported math proficiency, and a day-of-the-week dummy, and ϵ_i is the robust error term. To test for associations between the preference measures 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 (OLS) regressions. In order to correct for multiple hypotheses testing, 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]

[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 S5.1 in the Supplementary Information) 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.

3. Results

3.1. Descriptive Statistics and Correlations

Fig. 1 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 only 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. Fig. S1.3 in the Supplementary Information shows that the distributions of pro-environmental behaviours enacted are overall comparable across different household sizes.

Fig. 2 presents the histograms of the 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 18.46 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 ($M = 2.63$, $SD = 0.41$; Cronbach's $\alpha = 0.84$). Panel D shows that participants invested on average in about three products that reduce the environmental impact and home improvements ($M = 2.87$, $SD = 1.69$).

Supplementary Information S2 presents the descriptive statistics of all individual survey items as well as the histograms showing the distributions of the seven preference measures that are included in the regressions.

Fig. 3 presents the zero-order correlations between the seven 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 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 the four measures of pro-environmental behaviour, and that positive reciprocity is associated with the two general pro-environmental measures. Based on their meta-study of psychological research on individual differences, Gignac and Szodorai (2016) recommend that $r = 0.10$ can be categorised as "relatively small", $r = 0.20$ as "typical" and $r = 0.30$ as "relatively large". According to this categorisation, the correlations between altruism and pro-environmental behaviour and separately positive reciprocity and pro-environmental behaviour can be interpreted as typical. Overall, the correlations between the preferences and pro-environmental measures suggest that the domain of social preferences is the strongest contender for predicting pro-environmental behaviour in our pre-registered analysis.

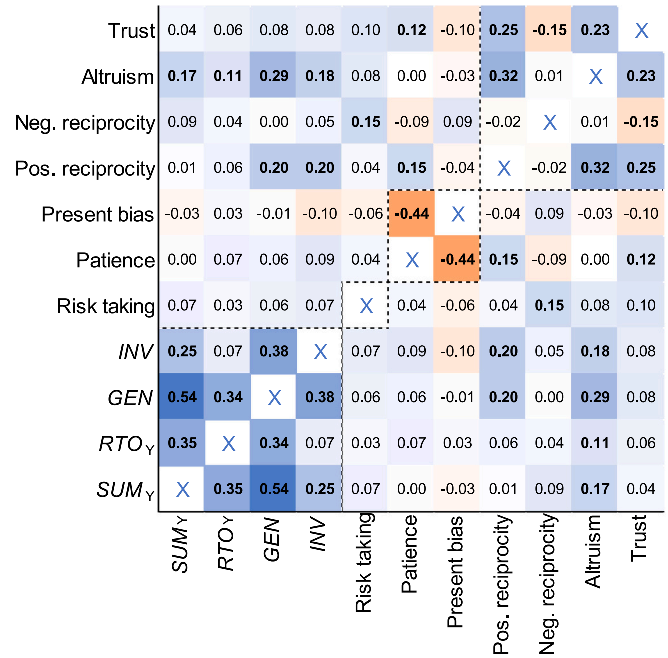

Fig. 3. Correlation matrix indicating Pearson's correlation coefficients between the measures of economic preferences and pro-environmental behaviour. Bold font indicates significance at $p < 0.05$.

3.2. Predicting Pro-environmental Behaviour

Table 1 shows the results of our ceteris paribus analysis regarding the explanatory power of the seven preference measures. The odd columns present the results of regressions that contain only the seven preference measures as independent variables. The even columns show the results of the pre-registered regression models with control variables. As the results are qualitatively similar, we focus on the results of the pre-registered models in the even columns. Overall, our results suggest that altruism, but no other preference measure, is associated with pro-environmental behaviour.

Altruism is a positive and highly significant predictor of the sum of pro-environmental behaviours enacted yesterday (Column 2; b = 1.428; $p = 0.005$). This suggests 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). A one standard deviation higher altruism score corresponds to a 7.7% increase over the mean of enacted pro-environmental behaviours. 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 4). This might suggest that participants with a higher altruism score are more likely to self-select into situations where pro-environmental behaviour is feasible, and once altruists are in such situations, they are no more or less likely than non-altruists to act pro-environmentally. However, there are problems with the outcome measure used in Columns 3 and 4 as discussed in Section 4.2.

Altruism does predict participants' general tendency to act pro-environmentally (b = 0.097; $p < 0.001$; Column 6). We find 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. This corresponds to a 3.7% increase over the mean for a one-standard deviation increase in altruism. The association between altruism and the number of long-term investments in green products (Column 8) is not significant using our Bonferroni-adjusted *p*-value (b = 0.243; $p = 0.011$), however positive reciprocity is. 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

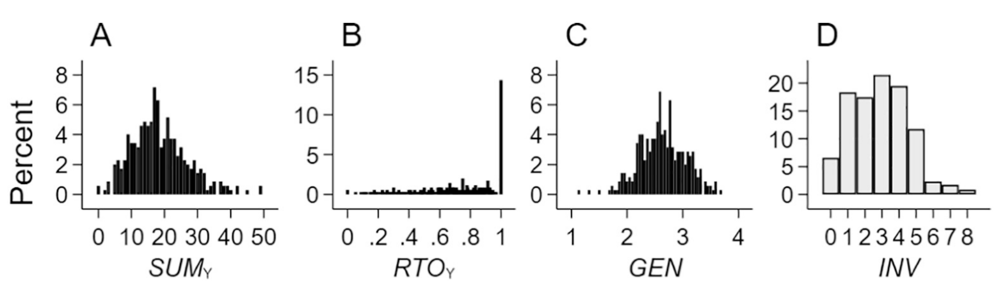

Fig. 2. Distribution of the four measures of pro-environmental behaviour.

Table 1
Predicting the four measures of pro-environmental behaviour.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	SUM_Y		RTO_Y		GEN		INV	
Risk taking	0.325	0.143	0.002	0.004	0.016	0.024	0.067	0.112
	(0.460)	(0.464)	(0.014)	(0.016)	(0.026)	(0.027)	(0.083)	(0.088)
Patience	−0.067	0.121	0.025	0.024	0.020	0.020	0.067	0.025
	(0.515)	(0.546)	(0.016)	(0.017)	(0.026)	(0.026)	(0.092)	(0.092)
Present bias	−0.288	−0.251	0.019	0.014	0.010	0.005	−0.125	−0.063
	(0.439)	(0.419)	(0.015)	(0.015)	(0.024)	(0.025)	(0.109)	(0.106)
Pos. reciprocity	−0.406	−0.228	0.001	0.008	0.048**	0.057**	0.264***†	0.186*
	(0.543)	(0.553)	(0.015)	(0.016)	(0.023)	(0.024)	(0.098)	(0.102)
Neg. reciprocity	0.759*	0.791	0.012	0.011	−0.003	−0.007	0.099	0.063
	(0.460)	(0.485)	(0.013)	(0.014)	(0.022)	(0.022)	(0.091)	(0.087)
Altruism	1.453***†	1.428***†	0.024*	0.022	0.103***†	0.097***†	0.213**	0.243**
	(0.524)	(0.506)	(0.014)	(0.015)	(0.024)	(0.023)	(0.088)	(0.095)
Trust	0.198	0.532	0.010	0.013	−0.006	−0.008	0.013	−0.061
	(0.460)	(0.467)	(0.013)	(0.014)	(0.021)	(0.022)	(0.085)	(0.089)
Control variables	No	Yes	No	Yes	No	Yes	No	Yes
Constant			0.687***	0.650***	2.632***	2.507***		
			(0.013)	(0.109)	(0.021)	(0.160)		
N	349	349	349	349	349	349	349	349
(Pseudo) R^2	0.019	0.063	0.025	0.094	0.098	0.235	0.0182	0.0429

Note. Columns 1, 2, 7, and 8 present the average marginal effects of Poisson regressions and thus constants are omitted. Columns 3–6 present the coefficients from OLS regressions. The robust *SE* are presented in parentheses. The control variables included in the even columns are age, gender, marital status, people living in household, education, income, math proficiency, and day of the week.
***† $p < 0.007143$.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

preference measure at a time. Supplementary Information S4 presents these analyses and shows that our results hold when not controlling for any of the other preferences in the regressions. Similarly, the multi-level regressions reported in Supplementary Information S5 confirm the results.

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 (the technical details of this analysis are provided in the Supplementary Information S6). This analysis explored the existence of 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 other pro-environmental forms of transportation like walking or cycling. The analysis indicates that 57% of the variance in the data can be explained by the following four components: Eco-shopping behaviours (“bought environmentally friendly products”, “bought products with less packing,” and “used reusable bags when shopping”), energy and water saving (“switched off electrical appliances”, “reduced heating”, “saved electricity in the house,” and “conserved water when it was not directly needed”), awareness behaviours (“talked to somebody about environmental issues” and “educated myself about the environment”), and reducing consumption and waste (“recycled”, “used a reusable cup/container for drinking,” and “made a product instead of purchasing it”).

After having identified the clusters present in the data, we predicted principal component scores for each cluster for each individual. These scores indicate the extent to which a given individual engaged in the behaviours represented by each component yesterday. We then used OLS regressions to test the predictive power of the seven preference measures for each of the component scores (Table 2). 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; p = 0.040). These results are robust to including only one preference measure at a time in the regression model (Supplementary Information Tables S6.2–S.6.5). Using the conservative Bonferroni-adjusted p-values, however, 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.

4. Discussion and Conclusion

4.1. Summary

This paper presents a pre-registered test of whether seven preference measures (risk taking, patience, present bias, altruism, positive reciprocity, negative reciprocity, and trust) predict pro-environmental behaviour in everyday life. Our main result is that only altruism, and none of the other economic preference measures, is systematically associated with pro-environmental behaviour in everyday life, predicting the extent of engagement in everyday pro-environmental behaviour as well as a general tendency to act pro-environmentally and past green investments. We also present evidence suggesting that the diverse range of everyday pro-environmental behaviours comprises of at least four distinct clusters (eco-shopping behaviours, electricity and water savings, awareness behaviours, and consumption and waste reduction) that are associated with different economic preference measures.

To assess the size of the association we find between altruism and pro-environmental behaviour in everyday life, we can compare our results with the results from other studies that use the same preference measure for altruism. However, while these studies use the same altruism measure, they use different behavioural outcome measures. Hence, we need to express our results on different scales to allow comparability. Moreover, there are only two studies that allow for a clean comparison with our data (Falk et al., 2018; Fuhrmann-Riebel et al., 2021).

Fuhrmann-Riebel et al. (2021) standardise their pro-environmental

Table 2
Ordinary least squares regression models predicting principal component scores of the pro-environmental behaviours 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	0.100	−0.137*	0.044
	(0.105)	(0.096)	(0.071)	(0.051)
Patience	0.001	−0.067	0.163**	0.096*
	(0.116)	(0.100)	(0.079)	(0.052)
Present bias	−0.085	0.003	0.043	0.070
	(0.091)	(0.097)	(0.071)	(0.046)
Pos. reciprocity	−0.088	0.237**	0.075	0.027
	(0.120)	(0.093)	(0.074)	(0.054)
Neg. reciprocity	0.190*	−0.082	0.075	−0.051
	(0.112)	(0.088)	(0.075)	(0.055)
Altruism	0.320**	0.012	0.052	0.007
	(0.125)	(0.088)	(0.068)	(0.051)
Trust	0.125	−0.104	−0.091	−0.015
	(0.108)	(0.087)	(0.074)	(0.051)
Control variables	*Yes*	*Yes*	*Yes*	*Yes*
Constant	2.840***	2.252***	0.137	−0.484
	(0.617)	(0.618)	(0.500)	(0.312)
N	349	349	349	349
R^2	0.138	0.124	0.107	0.109

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

behaviour measures and use OLS regressions to test for associations between altruism and these standardised measures. They find that the associations differ across the measures of pro-environmental behaviour: A 1 *SD* higher value of altruism is not significantly associated with sustainable plastic consumption and electricity spending, but it is significantly associated with a 0.220 *SD* increase in energy-saving behaviours. This latter association is similar in size to the association we find when repeating the analysis presented in column (2) of Table 1 with a standardised outcome measure; this analysis finds that a 1 *SD* higher value of altruism is significantly associated with a 0.172 *SD* increase in the sum of pro-environmental behaviours enacted yesterday.

Additionally, we can compare the size of the association between altruism and pro-environmental behaviour in our data with associations found in other papers between the same altruism measure and different behaviours that are theoretically linked to altruism but not usually considered "pro-environmental". Falk et al. (2018) report that a 1 *SD* increase in altruism is associated with a 15–20% higher probability of engaging in selected pro-social activities (compared to the baseline probability), such as donating, volunteering time, helping strangers, or sending money or goods to other people in need. In comparison, in our data a 1 *SD* increase in altruism is associated with a 7.7% higher sum of pro-environmental behaviours enacted yesterday compared to the mean (based on model 2 in Table 1), suggesting that we find a more modest association.

4.2. What Explains the Low Number of Significant Associations Between Economic Preferences and Pro-environmental Behaviour?

Several factors might explain the low number of significant associations between economic preferences and pro-environmental behaviour reported in this study. First, it is possible that our participants did not consider the riskiness, the timing, and some social characteristics of the behaviours when making environmentally relevant decisions. This explanation is in line with literature demonstrating that objective riskiness can differ from people's perceptions and attitudes towards risk (Charness et al., 2020; Slovic, 1987). While it may objectively be risky (not) to engage in a pro-environmental behaviour, participants may not have perceived this risk. On the other hand, participants may have understood the pro-environmental behaviours as benefiting others which may explain the significant association between altruism and pro-environmental behaviour. Future research should explicitly measure the extent to which people view behaviours as risky, take temporal dimensions into account, and consider social elements of the behaviours.

An additional explanation for the relatively modest associations between economic preferences and everyday pro-environmental behaviours reported in this study is that our main outcome variables were indices based on twenty structurally different behaviours. This may hide that some individual pro-environmental behaviours can be predicted by economic preference measures as shown in previous studies (Alpizar et al., 2008; Fuerst and Singh, 2018; Fuhrmann-Riebel et al., 2021; He et al., 2019) as well as our exploratory analysis. For example, we show that altruism predicts eco-friendly shopping (potentially because this relatively expensive type of shopping has benefits that are shared with others) and that patience predicts engagement in activities to raise pro-environmental awareness (possibly because their positive impacts will occur in the future). Aggregating over structurally different pro-environmental behaviours may have hidden any systematic underlying variation related to the riskiness, timing, and influence on others of the behaviours, and future research should incorporate structural differences in the analysis. More generally, future research should investigate the role of moderating factors (such as the structural aspects related to risk, time, and other people but also the difficulty of enacting behaviours, whether people consider the behaviours as pro-environmental, the domain of the preference measure, whether alternatives for the behaviours exist, and so on) that may explain when we do (and do not) find significant correlations between economic preference measures and pro-environmental behaviour.

It may also be the case that the use of self-reported measures of economic preferences affects our results. A common criticism of non-incentivised preference measures is that they suffer from hypothetical bias. This bias may be particularly strong when measuring altruism as people may prefer to present themselves as being altruistic. However, the survey instruments we used to assess preferences were developed based on their ability to capture behaviour in incentivised experiments (Falk et al., 2016). Hence, we would expect the preference measures to outperform traditional survey questions and capture valuable information about individuals' underlying preferences. In addition, there is empirical evidence suggesting that these preference measures predict a wide range of theoretically relevant behaviours, such as self-employment, smoking, saving behaviour, educational attainment, donations, and volunteering (Falk et al., 2018).

A similar criticism may apply to self-reported measures of pro-environmental behaviour, which may overstate actual behaviour if participants want to signal to themselves and to others how pro-environmental they are. Existing research examining this issue, however, has documented negligible correlations between social desirability and self-reported pro-environmental behaviour scales (Milfont, 2009). Our use of the day reconstruction method to ask participants whether they had engaged in certain behaviours yesterday further attenuates this cause for concern. The specific character of these questions reduces the scope for social desirability bias and increases self-report accuracy by facilitating recall from people's episodic memory (Schwarz et al., 2009; Lange and Dewitte, 2019). Hence, at least compared to more traditional survey questions, we would expect our self-reports of pro-environmental behaviour to be less biased.

Despite the improvements over standard survey measures reflected in both our preference and everyday pro-environmental measures, some issues relating to external validity remain. First previous research suggests that social preferences (Fleiß et al., 2019), risk preferences (Riddel, 2012; Weber et al., 2002), and time preferences (Augenblick et al., 2015) can differ depending on the domain (e.g., money, effort, health, and environment) in which they are elicited. As a result, our findings may be influenced by our linking general, rather than environment-related, preference measures to pro-environmental behaviour. Second, the day reconstruction method as a measure of pro-environmental behaviour has not yet been validated against other experience sampling methods and a recent study shows that there are differences between the two methods (Lucas et al., 2020). Finally, as both our preference and pro-environmental behaviours are captured using non-incentivised survey measures the significant correlation between altruism and pro-environmental behaviour that we observe in our data may be driven by a common method bias. Future research should look to incorporate incentivised and domain-specific preference measures, as well as experience sampling and objective measures of pro-environmental behaviour, to order to address these issues.

The finding that no preference measure predicts the intensity of pro-environmental behaviour (i.e., the ratio of enacted over feasible pro-environmental behaviours) may be related to measurement problems associated with this index. First, the index does not differentiate between participants who enact many pro-environmental behaviours from those who only enact few behaviours. Enacting all feasible behaviours yields the maximum score of 1, independent of whether the number of behaviours enacted is low or high. Second, this index is likely to overestimate the extent of conscious pro-environmental actions, because participants who reported engaging in a specific behaviour may not have had the opportunity to do otherwise. Finally, the index contains two self-reported elements (the possibility of enacting a behaviour and whether it was enacted or not) making it possibly twice as prone to hypothetical bias. Specifically, whether a pro-environmental behaviour is viewed as feasible by a participant may also be influenced by their risk, time, or social preferences.

4.3. Contributions to the Literature

The present paper contributes to the literature on the determinants of pro-environmental behaviour by using aggregate indices of pro-environmental behaviour to avoid effects driven by single behaviours, by estimating effect sizes of preference measures while controlling for other preference measures, and by capturing everyday high-frequency pro-environmental behaviours using the day reconstruction method. The literature on the determinants of pro-environmental behaviour shows, for example, that personality traits (Markowitz et al., 2012), green identity (Akerlof and Kranton, 2000; Binder and Blankenberg, 2017; Whitmarsh and O'Neill, 2010), sense of control (Gifford and Nilsson, 2014), social norms (Farrow et al., 2017), and the difficulty of enacting a behaviour (Kaiser and Keller, 2001) explain engagement in pro-environmental behaviour. Most closely related to ours are studies reporting that economic preferences predict single pro-environmental behaviours (Fuerst and Singh, 2018; Fuhrmann-Riebel et al., 2021; He et al., 2019; Newell and Siikamäki, 2015; Schleich et al., 2019).[3] Our results add to this literature by showing that altruism (but none of the other economic preferences we measured) predicts aggregate measures of everyday pro-environmental behaviour. This suggests that these behaviours are predominantly perceived as prosocial.

We also contribute to the literature on the external validity of economic preference measures (Levitt and List, 2007). For example, Galizzi and Navarro-Martinez (2018) report only weak correlations between laboratory measures of social preferences and relevant field behaviours such as donating and helping others. Similarly, Delaney and Lades (2017) do not find evidence for a correlation between present bias and everyday self-control failures; Goeschl et al. (2020) find that behaviour in public good games accounts for voluntary mitigation decisions only under certain circumstances; and Charness et al. (2020) find no significant associations between laboratory measures of risk attitudes and relevant behaviours in the field. Our results are in line with this literature.

The paper also suggests that the day reconstruction method is a useful tool to measure pro-environmental behaviour. Thus, the paper contributes to the literature that predominantly employs traditional questionnaire measures of pro-environmental behaviour by showing that it can also be measured efficiently in everyday life (Lange and Dewitte, 2019; Melo et al., 2018; Schmitt et al., 2018; Whitmarsh and O'Neill, 2010). While most previous research focuses on the self-reported general tendencies to behave pro-environmentally, we show that it is possible to quantify pro-environmental behaviour in everyday while minimising recall bias (see also Baumgartner et al., 2019).

Finally, our results have potential implications for future research that aims to inform policy. Policy interventions to encourage everyday pro-environmental behaviour should focus on testing messages that highlight the altruistic character of this behaviour. Furthermore, structural differences in the diverse range of everyday pro-environmental behaviours suggest that testing several targeted interventions aimed at different clusters of behaviours may lead to more effective interventions.

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Declaration of Competing Interest

None.

[3] The paper by Fuhrmann-Riebel et al. (2021) also investigates the role of economic preferences for pro-environmental behaviour. While this 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, and they investigate the topic as part of a large survey in Peru. Their general result, that different preferences matter for different pro-environmental behaviours, however, is in line with our findings.

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Appendix A. Supplementary Data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolecon.2021.106977.

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