nature human behaviour

ARTICLES

https://doi.org/10.1038/s41562-021-01095-8

Check for updates

An experimental test of fundraising appeals targeting donor and recipient benefits

John A. List[1,2,3], James J. Murphy[4]✉, Michael K. Price[2,3,5] and Alexander G. James[4]

We partnered with Alaska's Pick.Click.Give. programme to implement a statewide natural field experiment with 540,000 Alaskans designed to examine two of the main motivations for charitable giving: concerns for the benefits to self (impure altruism or 'warm glow') or concerns for the benefits to others (pure altruism). Our empirical results highlight the relative importance of appeals to self: individuals who received such an appeal were 6.6% more likely to give and gave 23% more than counterparts in the control group. Yet, a message that instead appealed to recipient benefits (motivated by altruism) had no statistically significant effect on average donations relative to the control group. We also find evidence of long-run effects of warm-glow appeals in the subsequent year. Our results have import for theoreticians and empiricists interested in modelling charitable giving as well as practitioners and policymakers.

Charitable organizations play an important role in modern economies, providing invaluable public goods and employment opportunities for millions across the United States. Not surprisingly, this has prompted substantial research on the primitives of the economics of charity and the relationship between charities and potential donors. Much of this work has focused on the impact of different fundraising techniques and the associated impact on both the number of donors and overall contribution levels. Such studies cover topics including: (i) matching gifts and rebates[1–6], (ii) charitable auctions and lotteries[7–11], (iii) social comparisons[12–14], (iv) thank-you gifts[15–17], (v) peer solicitations[18–20] and (vi) seed money announcements[21–25]. Our study builds on this body of work and takes as inspiration studies that highlight the importance of warm glow[26–33] and a related literature in marketing exploring the effectiveness of solicitation appeals highlighting benefits to self[34–37]. Although the warm-glow model[38,39] is the canonical example, other models that focus on the relative importance of benefits to self include work on social pressures[40–43] and social identity[44,45].

Our goal is to extend this work by examining whether targeted messages and normative appeals affect donor behaviour and uncover the motives for giving. To do so, we embedded a natural field experiment within Alaska's Permanent Fund Dividend (PFD) annual registration process. The PFD represents an individual's share of the earnings that the state receives from investing oil revenues. Any individual (including children) who was an Alaska resident for the entire calendar year prior, and who declares an intent to remain in the state indefinitely, is eligible to receive a dividend. The registration period begins every 1 January and continues through the final day of March, with distribution of the PFD occurring in early October. From 2009 to 2015, the PFD ranged between US$878 and US$2,072; in 2014, the year of our study, the PFD was US$1,884. Potential recipients must register for the PFD on an annual basis to confirm their eligibility. Those individuals who file online (~83% of applicants) have the option to voluntarily donate a portion of their PFD to Alaskan nonprofits through a programme known as Pick.Click.Give., which was established in 2009. The minimum allowable donation is $25, increasing in $25 increments up to the full amount of the PFD. Although the PFD application process is limited to the first quarter, the Pick.Click.Give. donation is a pledge that can be amended through 31 August, at which time it becomes a binding commitment. Additional details about the PFD and Pick.Click.Give. are provided in the Supplemental Information.

We randomly assigned every household in Alaska to either a control group (no postcard) or one of two treatment groups that received a postcard (Fig. 1) that included a normative appeal designed to highlight one of two main motivations for charitable giving: concerns for the benefits to self (impure altruism or 'warm glow') or concerns for the benefits to others (pure altruism). Figure 2 shows the spatial distribution of our treatments throughout the state. Anchorage, Juneau, Fairbanks and Kodiak Island had multiple zip codes; each of the other communities only had a single zip code and was thus exposed to a single treatment condition.

The results from our experiment highlight the relative importance of benefits to self in donation decisions. Individuals who received the benefits to self message were approximately 6.6% more likely to give and their contributions were 23% larger compared with the control group. Messages that highlighted the benefits to others increased the propensity to give, but there was no evidence of an effect on average donation size. As in Landry et al.[46], we found that prior donors were more likely to give and provided larger average gifts than cold-list counterparts. However, we also found that estimated treatment effects on both the propensity to give and average donation size were more pronounced amongst cold-list households, suggesting that normative appeals are an effective way to attract new donors.

Given past work showing the relative impermanence of behavioural interventions[46–49] and the importance that charitable organizations place on building a long-term relationship with donors, it is important to explore whether the effects of our targeted messages are sustained across campaigns. To provide insights into the long-run impacts, we examined whether treatment assignment in 2014 impacted contributions during the 2015 campaign. The results

[1]Department of Economics, University of Chicago, Chicago, IL, USA. [2]National Bureau of Economic Research, Cambridge, MA, USA. [3]College of Business and Economics, Research School of Economics, Australian National University, Canberra, Australian Capital Territory, Australia. [4]Department of Economics, University of Alaska Anchorage, Anchorage, AK, USA. [5]Department of Economics, Finance and Legal Studies, Culverhouse College of Commerce, University of Alabama, Tuscaloosa, AL, USA. ✉e-mail: jjmurphy2@alaska.edu

Fig. 1 | Treatment postcards. a,**b**, Images printed on standard-sized postcards to achieve framing by treatment for benefits to self (**a**) and benefits to others (**b**). The Pick.Click.Give. programme granted permission to use the content shown in the figures.

of this analysis suggest that our intervention impacted long-run patterns of giving: those who received the benefits to self message were more likely to give and provided larger contributions in 2015 than others. However, persistence differed across donor types. For warm-list donors, the effectiveness of our 'nudge' waned over time and had little impact on giving in the 2015 campaign. For cold-list donors, treatment effects were more persistent and suggest that receiving the benefits to self message had long-lasting effects.

Our paper contributes to several different literatures and extends previous work along two dimensions. We explore the impact of targeted messages and normative appeals on charitable giving in a natural field experiment. In this regard, our paper shares similarity with research exploring the impact of social information on contributions to a charity or online message board[12,13,20,50–52]. Moreover, prior work has focused on behaviour in the context of a fundraising drive to explore how various strategies affect giving to a specific cause. Our study, in contrast, explores behaviour in the context of a government-sponsored programme designed to encourage giving to a range of eligible charitable organizations and how our messages impacted aggregate patterns of giving through this programme. In this regard, our study is closest in spirit to an emerging literature that explores the use of social norms to induce uptake of in-home energy audits as a means to promote the adoption of improved technologies[53–55]. More broadly, our findings contribute to the literature on social norms and the use of normative appeals to promote behavioural change. This literature has largely focused on using such appeals to influence outcomes such as retirement savings and the use of credit[56,57], tax compliance[58,59], traffic violations[51] or the amount of water or energy used by residential households[48,49,60–65].

Second, our paper contributes to a body of research in marketing and social psychology exploring the impact of self- and other-benefit appeals on charitable donations[35–37,66]. However, much of this literature relies upon laboratory experiments and hypothetical decisions such as statements about one's intention to donate to a given cause. Moreover, the aim of this literature is to explore whether factors such as self-image concerns, public observability or social exclusion moderate the effectiveness of such appeals. Our paper extends this literature by exploring the impact of such appeals on both contemporaneous and long-run patterns of giving in a field setting.

Third, our paper contributes to a literature exploring the economic impacts of universal cash transfers such as Alaska's PFD payments. This literature has focused on how receipt of the PFD payments impacts outcomes such as intertemporal patterns of consumption[67,68], short-term mortality[69], aggregate employment[70] or crime[71]. We extend this literature by exploring how the PFD payments influence charitable giving and the private provision of public goods.

Finally, our paper contributes to a literature that sets forth to identify the underlying motives for charitable giving. Broadly speaking, such studies focus on two main drivers of behaviour, that is, concerns for the benefits to self or concerns for the benefits to others, and attempt to disentangle the motives by testing the extent to which donations by others are a substitute for one's own gifts. For example, there is a rich body of work that relies upon variation in the gifts of others and government funding to test for crowding[27,32,72–78]. Although such an approach tests the defining characteristic of the pure altruism model (complete crowding), identification requires strong assumptions regarding fundraising effort and what is known by potential donors regarding the gifts of others. Our study provides an alternate approach to disentangle the relative importance of benefits to self and benefits to others, that is, the use of targeted messages that make salient a given motive.

Results

Overall, in 2014, approximately 4.9% of all individuals gave more than US$3.1 million (~US$5.79 per person) to the nonprofit organizations registered with Pick.Click.Give. Relative to the 2013 campaign, these figures correspond to an approximate 9.3% increase in the total number of donors and a 23.9% increase in total US$ raised (which partly reflects an increase in PFD registrations from 2013). Table 1B shows that 4.4% (or 7,552) of the individuals in the control group donated a portion of their PFD, and they donated a total of US$807,548 or approximately US$4.765 per person (s.d. 0.206). Those individuals who received the benefits to self message were approximately 29.5% more likely to give (5.7% versus 4.4%) than were counterparts in the control group (95% CI [0.004, 0.021], $P=0.001$). Moreover, average contributions for those in the benefits to self treatment were approximately 54.3% greater (US$7.36 versus US$4.77) compared with control group (95% CI [1.051, 4.135], $P=0.001$). This leads to our first set of results and provides evidence that targeted messages, particularly those that emphasize warm-glow motivations, influence charitable contributions:

Result 1: Individuals receiving the benefits to self message ('Warm Your Heart') were more likely to give and provided larger gifts than those in the control group.

This first result shares similarity with prior work showing the influence of normative appeals on behaviours such as environmental conservation[48,79,80], honesty in markets[81] or tax compliance[59]. Result 1 also shares similarity with work in marketing showing that self-benefit appeals increase the frequency with which laboratory subjects express willingness to support a charitable cause[35–37]. More broadly, our data suggest the importance of self-interest as a driver of donor behaviour, a finding consonant with prior work showing the importance of motives such as prestige and concerns for social image[52,82–86] or the impact of donor gifts or other private benefits linked to the contribution itself[8–11,45,87–90].

Empirical estimates presented in Fig. 3b provide additional support for the unconditional analysis discussed above. Treatment effects are estimated using a difference-in-differences estimation strategy in which 2013 is the reference year. In 2014, households in the benefits to self treatment donated approximately US$1.10 ($\beta_{2,2014}=1.095$, 95% CI [0.493, 1.697], $P=0.001$) more than they otherwise would have (see Supplementary Table 4 for a more detailed set of estimation results and hypothesis tests underlying Fig. 3). This represents a 23% increase in average donations relative to the approximate US$4.766 average gift in 2014 from counterparts in the control group. With 183,215 online filers in the benefits to self group donating an additional US$1.10, distributing this message raised an estimated US$201,536. Had all online filers received this message, we estimate that Pick.Click.Give. would have raised an additional US$594,136.

To provide insights into the factors that influence an individuals' decision about whether to contribute through Pick.Click.Give., we estimate the linear probability of the contribution decision of individuals who registered for PFD online. Empirical estimates are

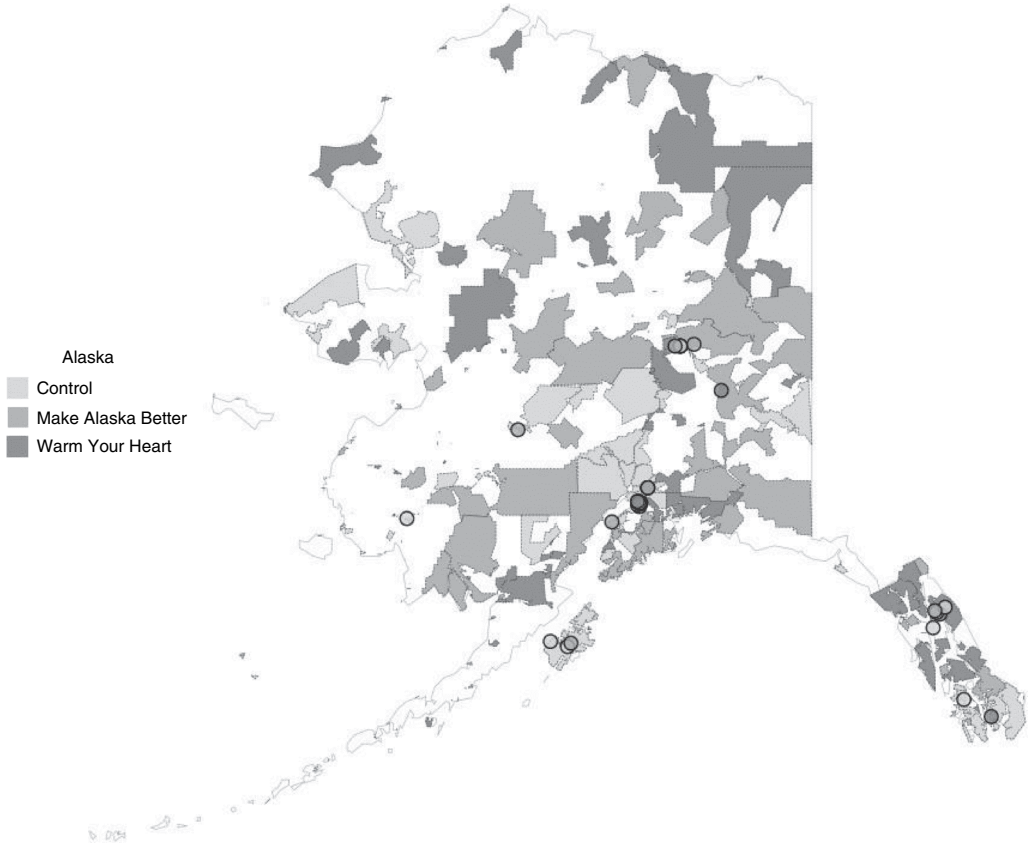

Fig. 2 | Geographic overview of treatment assignment. Alaskan zip codes shaded according to their random treatment assignment to the no-postcard control group (light grey), benefits to others postcard (medium grey, Fig. 1b) and benefits to self postcard (dark grey, Fig. 1a). White spaces indicate national parks or areas with very low population density, which were excluded from the randomization. Circles represent PO boxes and their respective treatment assignment.

presented in Fig. 4 and again indicate that messages that make salient self-interest influence the decision to donate (see Supplementary Table 5 for a more detailed set of estimation results and hypothesis tests underlying Fig. 4). For example, referring to Fig. 4b, we find that exposure to the benefits to self postcard in 2014 caused a 0.3 percentage point (approximately 6.6%) increase in the propensity to give ($\beta_{2,2014}=0.003$, 95% CI [0.001, 0.005], $P=0.002$).

We next explore the effect of our benefits to others appeal. From Supplementary Table 3, the average donation among people in the benefits to others group (US$5.21) was similar to that in the control group (US$4.77); there is no evidence of a difference in the average donation between these groups (95% CI [−1.283, 2.171], $P=0.612$). We find that participation rates were similar across the two groups (4.53% versus 4.46%). There is no evidence of a difference in participation rates between these groups (95% CI [−0.008, 0.010], $P=0.871$). However, comparing unconditional means can obscure important pre-existing differences in giving across treatments. To complement these raw statistics, we return to the empirical estimates presented in Figs. 3 and 4, which present linear regression models exploring the impact of treatment on average contributions and underlying rates of giving, respectively. Figure 3a,b show that exposure to the benefits to others treatment in 2014 increased the average donation size by US$0.32 ($\beta_{1,2014}=0.320$, 95% CI [−0.301, 0.943], $P=0.311$). The difference in treatment effects was approximately 0.77 ($\beta_{2,2014}-\beta_{1,2014}=0.774$, 95% CI [0.110, 1.438], $P=0.023$), suggesting that exposure to the benefits to self treatment was more effective at increasing average donations than the benefits to others treatment. Because differences in treatment effects are linear combinations of multiple parameter estimates from the baseline estimation equation, the delta method was used to construct confidence intervals (see Supplementary Tables 4 and 5 for a more detailed set of results regarding average contributions and the propensity to donate).

Considering average participation rates, Fig. 4a,b shows no evidence of a difference in the likelihood of giving between those in the benefits to self and benefits to others treatments in 2014 ($\beta_{2,2014}-\beta_{1,2014}=0.0007$, 95% CI [−0.001, 0.003], $P=0.472$). Relative to 2013, people in both groups were more likely to contribute than those in the control ($\beta_{1,2014}=0.002$, 95% CI [0.0003, 0.004], $P=0.025$; $\beta_{2,2014}=0.003$, 95% CI [0.001, 0.005], $P=0.002$).

Viewed in its totality, these data suggest a second result:

Result 2: The benefits to others message had the same positive contemporaneous impact on the likelihood of giving as the benefits to self message, but there is no evidence that it had an effect on average donation size relative to the control.

Heterogeneity in the response to the benefits to self and benefits to others treatments provides evidence that donors were responding to the content of our messages and not only the receipt of a message highlighting Pick.Click.Give. Importantly, this allows us to rule out models such as bounded rationality[91,92] or observation ('Hawthorne') effects[93] as, under any such model, the act of receiving a targeted message advertising Pick.Click.Give. should lead to increased donations. Hence, we would expect to observe treatment effects in both treatment groups.

Taken together, our first two results provide evidence that targeted messages and normative appeals can influence donor

Table 1 | Summary statistics for 2014 treatment assignment

Panel A: 2013	Control	Others	Self
Individuals	152,916	165,377	164,871
Donors	7,103	7,589	9,644
Donation rate	0.046	0.045	0.058
Total donations	648,475	733,300	999,875
Average donation: all	4.24	4.434	6.064
Average donation: PCG donors	91.30	96.63	103.68
Panel B: 2014 (year of treatment)			
Individuals	169,441	187,468	183,215
% female	0.494	0.498	0.497
Avg. age	35.78	34.98	35.86
Donors	7,552	8,498	10,560
Donation rate	0.044	0.045	0.057
Donation rate (warm list)	0.563	0.572	0.590
Donation rate (cold list)	0.013	0.014	0.017
Total donations	807,548	976,725	1,348,310
Average donation: all	4.765	5.209	7.358
Average donation: PCG donors	106.93	114.94	127.68
Average donation (warm list)	66.44	73.63	82.70
Average donation (cold list)	1.113	1.223	1.668
Zip codes	89	90	89
Panel C: 2015			
Individuals	154,169	167,359	166,441
Donors	9,304	9,985	12,298
Donation rate	0.060	0.059	0.073
Total donations	941,137	1,084,536	1,464,782
Average donation: all	6.10	6.48	8.80
Average donation: PCG donors	101.15	108.62	119.11

Note: Summary statistics are presented for campaign years 2013 (panel A), 2014 (panel B) and 2015 (panel C). All cell entries are based on the random treatment assignment for the 2014 PFD registration campaign. Treatment postcards were only delivered for the 2014 PFD registration. Statistics are for online filers only. Warm list (cold list) donors gave at least once (not even once) from 2011 to 2013. "Average donation: all" is the average donation dof both donors and non-donors combined. "Average donation: PCG donors" is the average amount donated, conditional on having donated to Pick.Click.Give. (PCG).

behaviour. However, the efficacy of such appeals depends upon the way in which the benefits of giving are framed. Donors are more motivated by appeals that highlight self-benefits than those that highlight how giving benefits others. Such differences are consistent with findings from the marketing literature showing the superiority of self-benefit appeals to give when the choice is made in private or in environments with low observability[35]. Moreover, our findings share similarity with prior work using tests of crowd-out to identify the relative importance of impure altruism or warm glow versus altruism and concerns for the wellbeing of others[27,32,72–78]. As in this prior work, donors in our experiment appear to be motivated more by self-benefit concerns than the wellbeing of others.

Before proceeding, we note that the observed differences in the effect of the benefits to self and benefits to others treatments on average contributions reflect heterogeneous effects of these treatments on conditional contributions. As shown in Fig. 3g,h, conditional on participation in Pick.Click.Give., individuals in the benefits to self group gave US$8.77 more than they otherwise would have ($\beta_{2,2014}=8.769$, 95% CI [0.526, 17.011], $P=0.037$). In contrast, the effect of the benefits to others treatment on conditional contributions was smaller (US$4.74) and not statistically significant ($\beta_{1,2014}=4.736$, 95% CI [−6.776, 16.247], $P=0.418$).

Our analysis thus far has examined behaviour pooled across all donor types. However, as noted in Landry et al.[46], there are important differences in behaviour across warm- and cold-list households: prior donors are more likely to give and are less responsive to both conditional and unconditional gifts. As we observe donations made through Pick.Click.Give. from 2011 to 2013, our data are sufficiently rich to allow us to explore heterogeneity across different donor types. To do so, we restrict our data to warm-list (those who gave at least once in 2011, 2012 and 2013) and cold-list donors (those who never donated in those years) and re-estimate our baseline equations. Results for these models suggest a third set of results:

Result 3a: Prior donors (warm list) were more likely to give and provided larger average gifts than prospective donors.

Result 3b: Among prospective (cold-list) donors, exposure to the benefits to self treatment increased average donation size and the propensity to give; there is no evidence that exposure to the benefits to others treatment had an effect.

Support for result 3a is provided in Table 1B. In 2014, average donations for warm-list individuals in the control group were approximately US$64 greater than that for cold-list, or prospective, donors (95% CI [57.21, 73.45], $P=0.001$). Much of this difference is explained by dramatic differences in participation rates. Whereas less than 2% of prospective donors gave through Pick.Click.Give., over half of all warm-list individuals elected to give. Model 2 of Supplementary Tables 4 and 5 conditions treatment effects on 2013 donation decisions and reinforces the idea that past donors were more likely to give and gave larger donations.

Support for result 3b is also provided in Figs. 3 and 4. For example, relative to 2013, in 2014, prospective donors in the benefits to self treatment provided average gifts that were approximately US$0.56 (39%) greater than those prospective donors observed in the control group ($\beta_{2,2014}=0.559$, 95% CI [0.189, 0.928], $P=0.003$). For prior donors, the relative effect of the benefits to self message was less pronounced: such people provided average gifts that were approximately 11% greater than they would have been in the absence of treatment ($\beta_{2,2014}=7.301$, 95% CI [2.39, 12.21], $P=0.004$). Importantly, both of these differences are statistically significant at conventional levels.

We observe similar data patterns when exploring participation rates. Referencing Fig. 4, relative to in 2013, in 2014, cold-list donors in the benefits to self treatment were 0.37 percentage points (roughly 22%) more likely to give than prospective donors in the control group ($\beta_{2,2014}=0.0037$, 95% CI [0.001, 0.006], $P=0.006$). For warm-list donors, the relative impact was again less pronounced. There was an approximately 6.2% increase in the likelihood of giving for a warm-list individual in the benefits to self treatment ($\beta_{2,2014}=0.035$, 95% CI [0.017, 0.054], $P=0.001$). As noted in Fig. 4, the effect of the benefits to others treatment on participation rates was driven entirely by warm-list households: whereas warm-list donors receiving the benefits to others message were significantly more likely to contribute than counterparts in the control group, there is no evidence of a difference in participation rates for prospect donors assigned to the benefits to others treatment and counterparts in the control group ($\beta_{1,2014}=0.0007$, 95% CI [−0.002, 0.003], $P=0.549$). Taken jointly, these differences suggest an interesting asymmetry. Whereas the benefits to self message impacted both prospective and prior donors, the effects (on both the propensity to donate and average donation size) were greatest for people who had not previously participated in Pick.Click.Give.

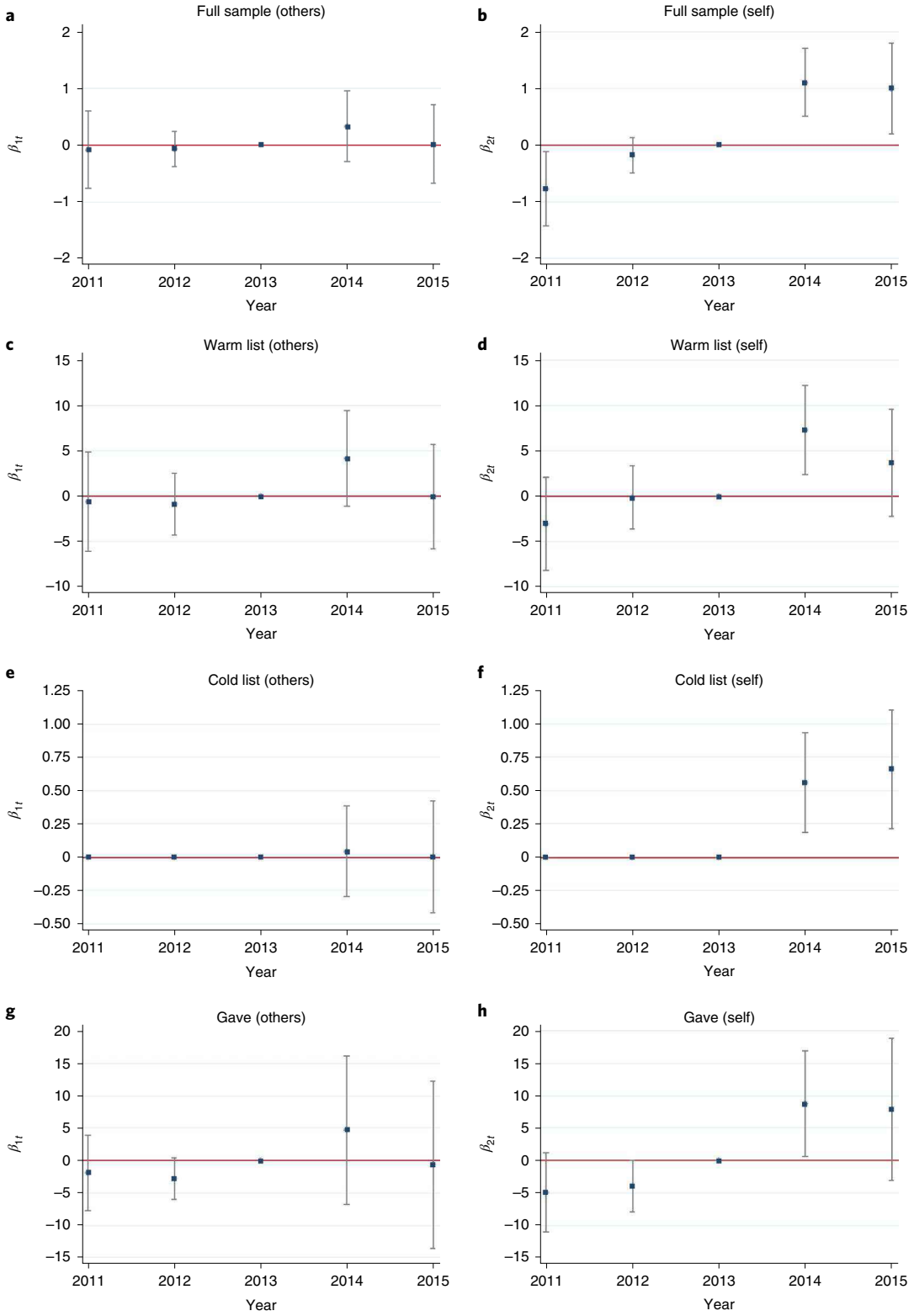

Fig. 3 | Donation size. a–h, Point estimates corresponding to β_{1t} and β_{2t} from estimation Eq. (1) for the full sample (**a**,**b**, $N = 1{,}888{,}875$) and restricted to people who gave at least once between 2011 and 2013 (**c**,**d**, $N = 139{,}125$), people who did not give between 2011 and 2013 (**e**,**f**, $N = 1{,}749{,}750$), and people who gave in both 2014 and 2015 (**g**,**h**, $N = 79{,}415$) when exposed to the benefit to others (**a**,**c**,**e**,**g**) or benefit to self treatment (**b**,**d**,**f**,**g**). All regressions include zip code and year fixed effects, and 2013 is the reference year. Errors are clustered at the zip code level, and 95% confidence intervals are shown as error bars. The red line indicates zero. Specific point estimates and a full set of statistics are provided in Supplementary Table 4.

A final result of interest concerns the impact of age and gender on donor behaviour. As noted in List[94], there are marked differences in generosity across men and women, particularly when exploring the behaviour of young men. As we observed data on the age and gender of every individual in our data, we can explore similar patterns. We augment our baseline specifications to include indicators

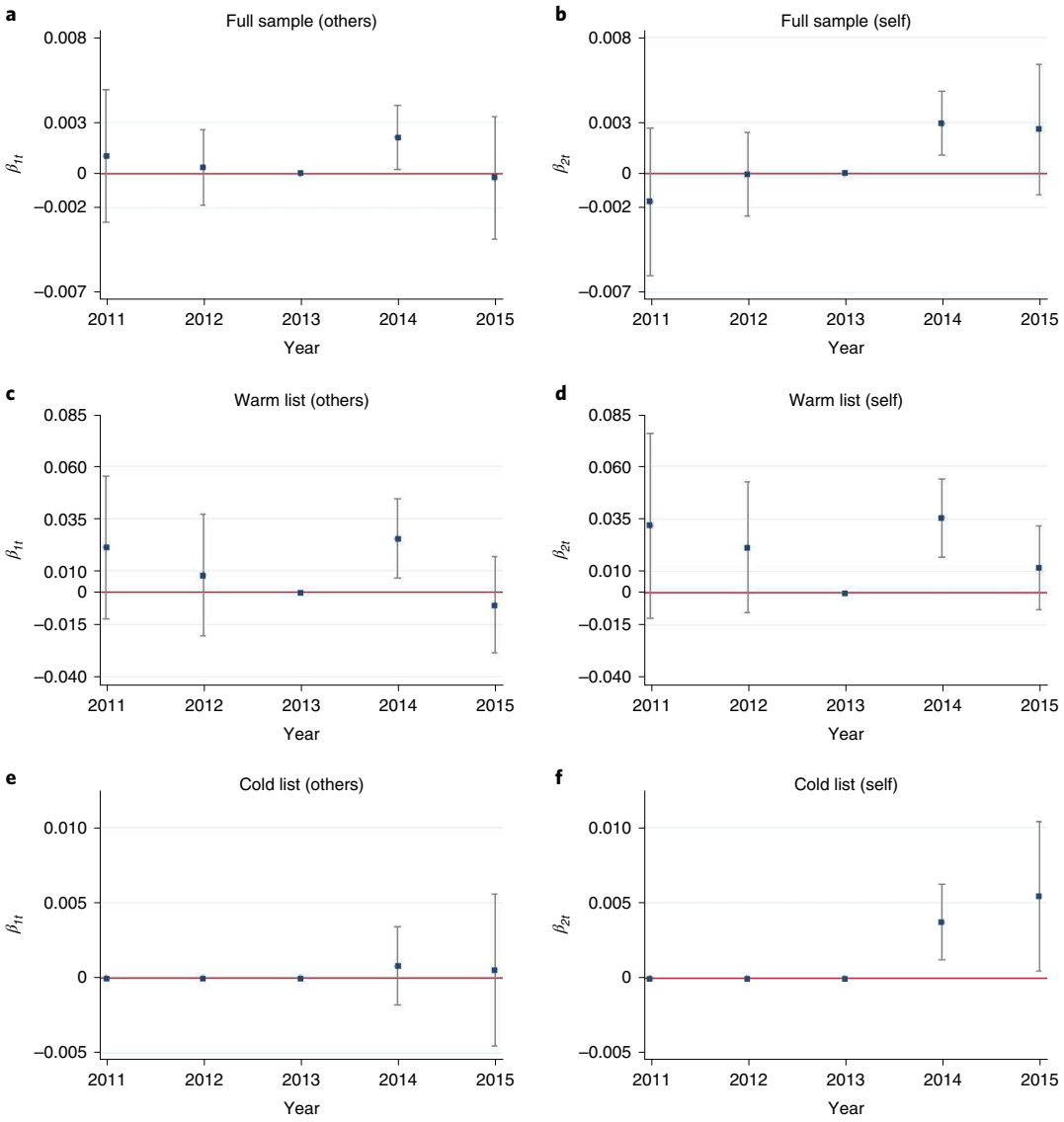

Fig. 4 | Propensity to give. a–f, Point estimates corresponding to β_{1t} and β_{2t} from estimation Eq. (1) for the full sample (**a**,**b**, $N=1{,}888{,}875$) and restricted to people who gave at least once between 2011 and 2013 (**c**,**d**, $N=139{,}125$), and people who did not give between 2011 and 2013 (**e**,**f**, $N=1{,}749{,}750$), when exposed to the benefits to others (**a**,**c**,**e**) or benefits to self treatment (**b**,**d**,**f**). All regressions include zip code and year fixed effects, and 2013 is the reference year. Errors are clustered at the zip code level, and 95% confidence intervals are shown. The red line indicates zero. Specific point estimates and a full set of statistics are provided in Supplementary Table 5.

for women, those 50 years or older, and those under the age of 18 years. Given that prior donors were more likely to give and provided larger average gifts than others, one may be concerned that these demographic effects are capturing differences in the likelihood that an individual had given in the past. To rule out such a possibility, we condition these demographic effects on whether a person gave in 2013.

As shown in model 2 of Supplementary Tables 4 and 5, we find significant differences in giving across the age distribution. For example, those aged 50 years or older were more likely to give ($\beta_{\text{mature}}=0.006$, 95% CI [0.005, 0.007], $P=0.001$) and provided larger gifts than other types of donor ($\beta_{\text{mature}}=2.725$, 95% CI [2.226, 3.223], $P=0.001$). In contrast, those under the age of 19 years were less likely to give ($\beta_{\text{young}}=-0.006$, 95% CI [−0.007, −0.005], $P=0.001$) and provided smaller gifts than others ($\beta_{\text{young}}=-1.251$, 95% CI [−1.491, −1.012], $P=0.001$). Exploring gender differences, we find data patterns consistent with DellaVigna et al.[95]: unconditional of 2013 giving, on average, women were more likely to give ($\beta_{\text{female}}=0.026$, 95% CI [0.024, 0.027], $P=0.001$) and provided larger gifts ($\beta_{\text{female}}=2.261$, 95% CI [2.005, 2.516], $P=0.001$) than men. However, conditioned on giving in 2013, we find that men provided similar-sized gifts ($\beta_{\text{female}}=0.0775$, 95% CI [−0.118, 0.273], $P=0.436$). Taken jointly, this suggests that the distribution of altruism for women was less disperse than the distribution for men, which is the precise pattern identified by the structural estimates in DellaVigna et al.[95]. There is a growing body of work showing that behavioural interventions tend to wane over time[46–49,96]. Within the context of charitable giving, evidence on the persistence of treatment effects is mixed. Several studies have found that fundraising mechanisms (interventions) have no or a perverse impact on long-run patterns of giving[4,13,15,46]. Other studies, in contrast, have provided evidence for habit formation and the persistence of treatment effects[46,97]. Therefore, it is important to explore whether the effects of our targeted messages are sustained across campaigns and impact long-run patterns of giving. To better ascertain the long-run impacts of our different messages, we use data

on treatment assignment in 2014 and examine whether this affects donations in 2015.

Exploring differences across those who received the benefits to self message in 2014 and those in our control group, we see the first evidence that treatment effects may persist. Figure 3b shows that, relative to counterparts who did not receive a message in 2014, average donations in 2015 for individuals in the benefits to self treatment were US$0.99 higher ($\beta_{2,2015}=0.991$, 95% CI [0.184, 1.798], $P=0.016$). However, there is no evidence of persistence in the propensity to donate ($\beta_{2,2015}=0.0026$, 95% CI [−0.001, 0.006], $P=0.181$). In contrast, for the benefits to others treatment, there is no evidence of persistence in 2015 in either average donations ($\beta_{1,2015}=0.005$, 95% CI [−0.686, 0.696], $P=0.988$) or the propensity to donate ($\beta_{1,2015}=-0.0002$, 95% CI [−0.003, 0.004], $P=0.890$).

Separating the data into cold- and warm-list individuals, persistence in the effect of receiving the benefits to self message was driven primarily by cold-list individuals. Relative to the control, such individuals were more likely to donate than they were in 2013 ($\beta_{2,2015}=0.005$, 95% CI [0.0004, 0.010], $P=0.033$) and they donated more on average ($\beta_{2,2015}=0.661$, 95% CI [0.215, 1.107], $P=0.004$). For warm-list donors, both average donations ($\beta_{2,2015}=3.678$, 95% CI [−2.272, 9.630], $P=0.224$) and the propensity to donate reverted to 2013 levels ($\beta_{2,2015}=0.012$, 95% CI [−0.007, 0.031], $P=0.230$).

These results suggest that the effect of the benefits to self message was persistent for first-time givers, which is consistent with results in Meer[97]. Yet, as in past work[13,15,48,49,96], the effectiveness of the benefits to others 'nudge' waned over time; subjects in this treatment group behaved no differently, on average, than they did in 2013.

Discussion

Enhancing the pool of charitable donations given to private providers of public goods has never taken on greater import. With record-high federal deficits and crumbling state and local budgets, the continuing devolution of goods and services will place even greater demands on the private provision of public goods and services. A growing body of literature sets forth to explore the economics of charity and the relationship between fundraisers and potential donors. Much of this work has focused on measuring the effectiveness of different fundraising techniques such as charitable lotteries or matching gifts that change the relative costs of benefits of giving. Our study extends this literature by exploring the effect of targeted messages and normative appeals on donor behaviour.

Results from our experiment highlight the relative importance of benefits to self as a driver of giving. Individuals who received the benefits to self message were approximately 6.6% more likely to give and donated approximately 23% more than counterparts in the control group. Messages that highlight the benefits to others, in contrast, had a similar impact on the likelihood of giving but had no impact on average donations. Interestingly, these same data patterns were observed for both warm-list households and cold-list counterparts, although the effects were more pronounced amongst cold-list households.

Pick.Click.Give. is one of a growing number of large-scale fundraising programmes that encourage philanthropy, such as Giving Tuesday and ArkansasGives. Such programmes are unique in that they do not solicit funds for a specific nonprofit. Rather, they provide a platform for donors to select causes to support from amongst a predetermined set of potential recipients. Our paper contributes to an emerging literature exploring behaviour in such contexts as opposed to exploring the response to an appeal to give to a single cause[97–99].

For academics, our results are noteworthy in that they provide a deeper understanding of individual behaviour and what drives the private provision of public goods. Importantly, our findings suggest that giving is motivated by self-interest rather than concerns for charitable output per se. For practitioners, our results are noteworthy in that they suggest ways to increase giving using simple messages that appeal to the donor's self-interest and the good feelings triggered by the act of giving. These findings are of particular interest to nonprofits in the State of Alaska and the design of the Pick.Click.Give. programme, which was established to increase overall giving statewide. If we had sent the benefits to self message to all households in the state, aggregate contributions would have increased by nearly US$600,000.

There are some potential limitations to these conclusions that warrant further investigation. Because Pick.Click.Give. is a fundraising programme and does not provide services itself, the benefits to others message had to be broad enough to encompass a wide range of activities provided by the various nonprofits, hence the appeal to 'Make Alaska Better for Everyone'. We cannot rule out the possibility that a more specific benefits to others appeal highlighting the charitable activities of a particular nonprofit or presenting an identifiable victim[100] would yield different results.

Finally, one might wonder about the external validity of our experimental results. To provide insight into this issue, we follow List[101] and present his selection, attrition, naturalness, scaling (SANS) conditions. First, in terms of selection, our sample includes the entire universe of Alaskan households, so there is no selection into the experiment. In terms of attrition, our compliance rates are 100%, as we observe donation decisions for every individual that filed online for PFD. Considering the naturalness of the choice task, setting and time frame, we use a natural field experiment[102]. Thus our setting is one in which subjects are engaged in a natural task and are not placed on an artificial margin. Yet, one should keep in mind that, beyond the message differences, it is also possible that individuals were more responsive to the heart image than the outline of the state map. Accordingly, our treatment should be considered a joint test of the message and the images across the two solicitation groups. Lastly, in terms of scaling our insights beyond the received sample and situation, since we view our main contribution as exploring the underpinnings of individual giving, future work should focus on replications to understand whether the result can be applied to other settings, populations and cultures more broadly. For example, we suspect that there will be important boundary conditions across societies[103], and perhaps the timing of the appeal might influence the observed treatment effects.

Methods

Ethics statement. The University of Alaska Anchorage Institutional Review Board determined that the study protocol met the U.S. Department of Health and Human Services requirements for the protection of human research subjects (45 CFR 46, as amended/revised) as being exempt from full board review. This was an observational study using publicly available data, the data do not include any personally identifying information, the investigators did not interact with study participants and the study presents no or minimal risk to participants. Therefore, the requirement for obtaining informed consent was waived.

Experiment design and implementation. As part of the 2014 Pick.Click.Give. fundraising campaign, we randomly allocated the approximately 290,000 households in Alaska to either a control group (no postcard) or one of two treatment groups that received a postcard promoting Pick.Click.Give. The postcards were designed in partnership with a marketing firm to include normative appeals that differed in whether the message highlighted either benefits to self ('Warm Your Heart', Fig. 1a) or benefits to others ('Make Alaska Better for Everyone', Fig. 1b). These same appeals were printed on the back of the postcard along with a montage showing pictures of various Alaska residents. Postcards were mailed during the last week of December 2013, and we received information on donations for each of the more than 540,000 Alaskans who registered for their 2014 PFD online during the first quarter of 2014. Mail-in PFD applicants were not eligible to donate through Pick.Click.Give. and are excluded from the data. We also excluded applications that were denied and did not receive a PFD. We observe total donations in excess of US$3.1 million from more than 26,000 unique individuals.

Since state law prohibited the PFD from providing address-level data, randomization occurred at the zip code level, with every household in a treatment zip code receiving one of two postcards (Fig. 1). We received individual-level data on donations made through Pick.Click.Give. for everyone who registered online

for PFD in 2013. The data included the zip code in which the individual resides, whether they donated some portion of their PFD to registered nonprofits, the name of the nonprofits supported and the amount shared with each selected nonprofit. We used data from contributions made through Pick.Click.Give. in 2013 to assign zip codes to treatment. For each individual, we aggregated the amount shared to get a total donation amount. We then used the aggregated data to calculate zip-code-level measures of average donations per individual and the fraction of individuals that shared their PFD—the outcomes upon which we randomized. We assigned zip codes to treatments to ensure balance along these two dimensions. Taking a conservative approach whereby each zip code provides a single observation, our resulting sample was powered to detect an effect size of approximately 0.42 standard deviation.

Households were assigned to treatments based on the zip code associated with an individual's mailing address. For a majority of the sample, home and mailing zip codes were the same. However, as college students and active military personnel were eligible for PFD, we observe a fraction of individuals for whom these zip codes did not match. Moreover, we do not observe whether an individual received or saw the postcard, which reduces the treatment effect if this is random. Finally, since there is a temporal delay between stimulus and response, time-varying moderators potentially lower the observed treatment effect. As a result, our estimates thus capture an intent-to-treat effect and provide a lower bound of the 'true' effect of treatment.

Table 1 summarizes the experimental design and corresponding sample size for each treatment. As noted in panel B, the control group included 169,441 individuals living in 1 of 89 distinct zip codes around the state. The benefits to others ('Make Alaska Better for Everyone') treatment included data for 187,468 individuals residing in 1 of 90 distinct zip codes around the state. The benefits to self ('Warm Your Heart') treatment included data for 183,215 individuals residing in 1 of 89 distinct zip codes around the state.

Data analysis. We estimate a series of linear regression models that explicitly control for observable and unobservable differences across potential donors. This analysis is important as such factors might systematically differ across treatment groups, leading to erroneous inference from a simple analysis of the raw data. For our baseline specification, we restrict the sample to the years 2011–2015, and only include those individuals who registered for PFD in all five years. We estimate a linear regression model of the amount contributed for each individual who registered for PFD online (including those who did not give) on indicator variables for our experimental treatments and other covariates:

$$D_{ijt} = \sum_{t \neq 2013} [\beta_{1t}\text{Others}_i + \beta_{2t}\text{Self}_i]Y_t + Y_t + Z_i + \epsilon_{ijt},$$

where D_{ijt} is the contribution level of the jth individual in the ith zip code in year t, Others_i is an indicator for receiving the benefits to others message and Self_i is an indicator for receiving the benefits to self message. Year and zip code fixed effects are given by Y_t and Z_i, respectively. Note that non-interacted indicators for treatment are captured by zip code and year fixed effects. As such, the estimated effect of receiving the benefits to others message in year t is given by β_{1t} and the effect of receiving the benefits to self message (β_{2t}) is similarly interpreted. These two coefficients are the estimated difference between the treatment and control in year t relative to the treatment–control difference in 2013 (that is, the year prior to treatment). Estimating this equation for pre-event years (2011 and 2012) reveals any pre-existing trends. We restrict our data to exclude the implementation phase of the Pick.Click.Give. programme (2009–2010). As can be seen from Supplementary Table 1, participation in the programme was not widespread until 2011. Further, widespread use of the programme occurred at slightly different times across zip codes and therefore treatments. Nonetheless, we reassuringly find minimal trend in the two years prior to the event date (2014). Because treatment is assigned at the zip code level, this specification allows us to estimate the effect of time-invariant individual-level characteristics, such as gender or historical patterns of giving. To account for unobservable heterogeneities at the zip code level, we cluster standard errors at the zip code level. We similarly model the individual decision to donate by replacing the outcome variable in the estimation equation above with an indicator equal to unity for individuals who donated. Unless otherwise stated, all hypothesis tests are two tailed. See the Supplementary Information for robustness checks of our results and conclusions.

Reporting summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

The data used in this study are available at https://osf.io/ycafq/.

Code availability

We used Stata version 16 for the data analysis. The Stata code is available at https://osf.io/ycafq/.

Received: 25 May 2020; Accepted: 8 March 2021;
Published online: 12 April 2021

References

1. Chen, Y. & MacKie-Mason, J. K. Online fund-raising mechanisms: a field experiment. *BE J. Econ. Anal. Policy* **5**, 4 (2006).
2. Eckel, C. C. & Grossman, P. J. Subsidizing charitable giving with rebates or matching: Further laboratory evidence. *South Econ. J.* **72**, 794–807 (2006).
3. Karlan, D. & List, J. A. Does price matter in charitable giving? Evidence from a large-scale natural field experiment. *Am. Econ. Rev.* **97**, 1774–1793 (2007).
4. Meier, S. Do subsidies increase charitable giving in the long run? Matching donations in a field experiment. *J. Eur. Econ. Assoc.* **5**, 1203–1222 (2007).
5. Huck, S. & Rasul, I. Matched fundraising: evidence from a natural field experiment. *J. Public Econ.* **95**, 351–362 (2011).
6. Scharf, K. & Smith, S. The price elasticity of charitable giving: does the form of tax relief matter? *Int. Tax. Public Financ.* **22**, 330–352 (2015).
7. Morgan, J. Financing public goods by means of lotteries. *Rev. Econ. Stud.* **67**, 761–784 (2000).
8. Goeree, J. K., Maasland, E., Onderstal, S. & Turner, J. L. How (not) to raise money. *J. Polit. Econ.* **113**, 897–918 (2005).
9. Landry, C. E., Lange, A., List, J. A., Price, M. K. & Rupp, N. G. Toward an understanding of the economics of charity: evidence from a field experiment. *Q. J. Econ.* **121**, 747–782 (2006).
10. Carpenter, J., Holmes, J. & Matthews, P. H. Charity auctions: a field experiment. *Econ. J.* **118**, 92–113 (2008).
11. Elfenbein, D. W. & McManus, B. A greater price for a greater good? Evidence that consumers pay more for charity-linked products. *Am. Econ. J. Econ. Policy* **2**, 28–60 (2010).
12. Frey, B. S. & Meier, S. Social comparisons and pro-social behavior: testing 'conditional cooperation' in a field experiment. *Am. Econ. Rev.* **94**, 1717–1722 (2004).
13. Shang, J. & Croson, R. A field experiment in charitable contribution: the impact of social information on the voluntary provision of public goods. *Econ. J.* **119**, 1422–1439 (2009).
14. Murphy, J. J., Batmunkh, N., Nilsson, B. & Ray, S. The impact of social information on the voluntary provision of public goods: a replication study. *Res. Exp. Econ.* **18**, 41–50 (2015).
15. Falk, A. Gift exchange in the field. *Econometrica* **75**, 1501–1511 (2007).
16. Alpizar, F., Carlsson, F. & Johansson-Stenman, O. Anonymity, reciprocity, and conformity: evidence from voluntary contributions to a national park in Costa Rica. *J. Public Econ.* **92**, 1047–1060 (2008).
17. Chao, M. Demotivating incentives and motivation crowding out in charitable giving. *Proc. Natl Acad. Sci. USA* **114**, 7301–7306 (2017).
18. Meer, J. Brother Can you spare a dime? Peer pressure in charitable solicitation. *J. Public Econ.* **95**, 926–941 (2011).
19. Castillo, M., Petrie, R. & Wardell, C. Fundraising through online social networks: a field experiment on peer-to-peer solicitation. *J. Public Econ.* **114**, 29–35 (2014).
20. Smith, S., Windmeijer, F. & Wright, E. Peer effects in charitable giving: evidence from the (running) field. *Econ. J.* **125**, 1053–1071 (2015).
21. Andreoni, J. Toward a theory of charitable fund-raising. *J. Polit. Econ.* **106**, 1186–1213 (1998).
22. List, J. A. & Lucking-Reiley, D. The effects of seed money and refunds on charitable giving: experimental evidence from a university capital campaign. *J. Polit. Econ.* **110**, 215–233 (2002).
23. Vesterlund, L. The informational value of sequential fundraising. *J. Public Econ.* **87**, 627–657 (2003).
24. Potters, J., Sefton, M. & Vesterlund, L. Leading-by-example and signaling in voluntary contribution games: an experimental study. *Econ. Theory* **33**, 169–182 (2007).
25. Bracha, A., Menietti, M. & Vesterlund, L. Seeds to succeed? Sequential giving to public projects. *J. Public Econ.* **95**, 416–427 (2011).
26. Andreoni, J. Warm-glow versus cold-prickle: the effects of positive and negative framing on cooperation in experiments. *Q. J. Econ.* **110**, 1–21 (1995).
27. Crumpler, H. & Grossman, P. J. An experimental test of warm glow giving. *J. Public Econ.* **92**, 1011–1021 (2008).
28. Null, C. Warm glow, information, and inefficient charitable giving. *J. Public Econ.* **95**, 455–465 (2011).
29. Tonin, M. & Vlassopoulos, M. Disentangling the sources of pro-socially motivated effort: a field experiment. *J. Public Econ.* **94**, 1086–1092 (2010).
30. Imas, A. Working for the 'warm glow': on the benefits and limits of prosocial incentives. *J. Public Econ.* **114**, 14–18 (2014).
31. Tonin, M. & Vlassopoulos, M. An experimental investigation of intrinsic motivations for giving. *Theory Decis.* **76**, 47–67 (2014).
32. Ottoni-Wilhelm, M., Vesterlund, L. & Xie, H. Why do people give? Testing pure and impure altruism. *Am. Econ. Rev.* **107**, 3617–3633 (2017).
33. Singh, J., Teng, N. & Netessine, S. Philanthropic campaigns and customer behavior: field experiments on an online taxi booking platform. *Manag. Sci.* **65**, 913–932 (2019).

34. Brunel, F. F. & Nelson, M. R. Explaining gendered responses to 'help-self' and 'help-others' charity ad appeals: the mediating role of world-views. *J. Advert.* **29**, 15–28 (2000).
35. White, K. & Peloza, J. Self-benefit versus other-benefit marketing appeals: their effectiveness in generating charitable support. *J. Mark.* **73**, 109–124 (2009).
36. Feiler, D. C., Tost, L. P. & Grant, A. M. Mixed reasons, missed givings: the costs of blending egoistic and altruistic reasons in donation requests. *J. Exp. Soc. Psychol.* **48**, 1322–1328 (2012).
37. Baek, T. H., Yoon, S., Kim, S. & Kim, Y. Social exclusion influences on the effectiveness of altruistic versus egoistic appeals in charitable advertising. *Mark. Lett.* **30**, 75–90 (2019).
38. Andreoni, J. Giving with impure altruism: applications to charity and Ricardian equivalence. *J. Polit. Econ.* **97**, 1447–1458 (1989).
39. Andreoni, J. Impure altruism and donations to public goods: a theory of warm-glow giving. *Econ. J.* **100**, 464 (1990).
40. DellaVigna, S., List, J. A. & Malmendier, U. Testing for altruism and social pressure in charitable giving. *Q. J. Econ.* **127**, 1–56 (2012).
41. Knutsson, M., Martinsson, P. & Wollbrant, C. Do people avoid opportunities to donate? A natural field experiment on recycling and charitable giving. *J. Econ. Behav. Organ.* **93**, 71–77 (2013).
42. Trachtman, H. et al. Fair weather avoidance: unpacking the costs and benefits of 'avoiding the ask'. *J. Econ. Sci. Assoc.* **1**, 8–14 (2015).
43. Andreoni, J., Rao, J. M. & Trachtman, H. Avoiding the ask: a field experiment on altruism, empathy, and charitable giving. *J. Polit. Econ.* **125**, 625–653 (2017).
44. Benjamin, D. J., Choi, J. J. & Strickland, A. J. Social identity and preferences. *Am. Econ. Rev.* **100**, 1913–1928 (2010).
45. Kessler, J. B. & Milkman, K. L. Identity in charitable giving. *Manag. Sci.* **64**, 845–859 (2018).
46. Landry, C. E., Lange, A., List, J. A., Price, M. K. & Rupp, N. G. Is a donor in hand better than two in the bush? Evidence from a natural field experiment. *Am. Econ. Rev.* **100**, 958–983 (2010).
47. Gneezy, U. & List, J. A. Putting behavioral economics to work: testing for gift exchange in labor markets using field experiments. *Econometrica* **74**, 1365–1384 (2006).
48. Ferraro, P. J. & Price, M. K. Using nonpecuniary strategies to influence behavior: evidence from a large-scale field experiment. *Rev. Econ. Stat.* **95**, 64–73 (2013).
49. Allcott, H. & Rogers, T. The short-run and long-run effects of behavioral interventions: experimental evidence from energy conservation. *Am. Econ. Rev.* **104**, 3003–3037 (2014).
50. Chen, Y., Harper, F. M., Konstan, J. & Li, S. X. Social comparisons and contributions to online communities: a field experiment on MovieLens. *Am. Econ. Rev.* **100**, 1358–1398 (2010).
51. Chen, Y., Lu, F. & Zhang, J. Social comparisons, status and driving behavior. *J. Public Econ.* **155**, 11–20 (2017).
52. Gallus, J. Fostering public good contributions with symbolic awards: a large-scale natural field experiment at Wikipedia. *Manag. Sci.* **63**, 3999–4015 (2017).
53. Hahn, R., Metcalfe, R. D., Novgorodsky, D. & Price, M. K. The behavioralist as policy designer: the need to test multiple treatments to meet multiple targets. *National Bureau for Economic Research* https://www.nber.org/papers/w22886 (2016).
54. Holladay, S., LaRiviere, J., Novgorodsky, D. & Price, M. Prices versus nudges: what matters for search versus purchase of energy investments? *J. Public Econ.* **172**, 151–173 (2019).
55. Allcott, H. & Greenstone, M. Measuring the welfare effects of residential energy efficiency programs. NBER Working Paper 23386 https://www.nber.org/papers/w23386 (National Bureau for Economic Research, 2017).
56. Beshears, J., Choi, J. J., Laibson, D., Madrian, B. C. & Milkman, K. L. The effect of providing peer information on retirement savings decisions. *J. Financ.* **70**, 1161–1201 (2015).
57. Seira, E., Elizondo, A. & Laguna-Müggenburg, E. Are information disclosures effective? Evidence from the credit card market. *Am. Econ. J. Econ. Policy* **9**, 277–307 (2017).
58. Fellner, G., Sausgruber, R. & Traxler, C. Testing enforcement strategies in the field: threat, moral appeal and social information. *J. Eur. Econ. Assoc.* **11**, 634–660 (2013).
59. Hallsworth, M., List, J. A., Metcalfe, R. D. & Vlaev, I. The behavioralist as tax collector: using natural field experiments to enhance tax compliance. *J. Public Econ.* **148**, 14–31 (2017).
60. Allcott, H. Social norms and energy conservation. *J. Public Econ.* **95**, 1082–1095 (2011).
61. Costa, D. L. & Kahn, M. E. Energy conservation 'nudges' and environmentalist ideology: evidence from a randomized residential electricity field experiment. *J. Eur. Econ. Assoc.* **11**, 680–702 (2013).
62. Asensio, O. I. & Delmas, M. A. Nonprice incentives and energy conservation. *Proc. Natl Acad. Sci. USA* **112**, E510–E515 (2015).
63. Brent, D. A., Cook, J. H. & Olsen, S. Social comparisons, household water use, and participation in utility conservation programs: evidence from three randomized trials. *J. Assoc. Environ. Resour. Econ.* **2**, 597–627 (2015).
64. Ito, K., Ida, T. & Tanaka, M. Moral suasion and economic incentives: field experimental evidence from energy demand. *Am. Econ. J. Econ. Policy* **10**, 240–267 (2018).
65. Brandon, A., List, J. A., Metcalfe, R. D., Price, M. K. & Rundhammer, F. Testing for crowd out in social nudges: evidence from a natural field experiment in the market for electricity. *Proc. Natl Acad. Sci. USA* **116**, 5293–5298 (2019).
66. Fisher, R. J., Vandenbosch, M. & Antia, K. D. An empathy-helping perspective on consumers' responses to fund-raising appeals. *J. Consum. Res.* **35**, 519–531 (2008).
67. Hsieh, C.-T. Do consumers react to anticipated income changes? Evidence from the Alaska Permanent Fund. *Am. Econ. Rev.* **93**, 397–405 (2003).
68. Kueng, L. Explaining consumption excess sensitivity with near-rationality: evidence from large predetermined payments. NBER Working Paper 21772 https://www.nber.org/papers/w21772 (National Bureau of Economic Research, 2015).
69. Evans, W. N. & Moore, T. J. The short-term mortality consequences of income receipt. *J. Public Econ.* **95**, 1410–1424 (2011).
70. Jones, D. & Marinescu, I. The labor market impacts of universal and permanent cash transfers: evidence from the Alaska Permanent Fund. NBER Working Paper 24312 https://www.nber.org/papers/w24312 (National Bureau of Economic Research, 2018).
71. Watson, B., Guettabi, M. & Reimer, M. Universal cash and crime. *Rev. Econ. Stat.* **102**, 678–689 (2020).
72. Kingma, B. R. An accurate measurement of the crowd-out effect, income effect, and price effect for charitable contributions. *J. Polit. Econ.* **97**, 1197–1207 (1989).
73. Andreoni, J. An experimental test of the public-goods crowding-out hypothesis. *Am. Econ. Rev.* **83**, 1317–1327 (1993).
74. Payne, A. A. Does the government crowd-out private donations? New evidence from a sample of non-profit firms. *J. Public Econ.* **69**, 323–345 (1998).
75. Andreoni, J. & Payne, A. A. Do government grants to private charities crowd out giving or fund-raising? *Am. Econ. Rev.* **93**, 792–812 (2003).
76. Andreoni, J. & Payne, A. A. Is crowding out due entirely to fundraising? Evidence from a panel of charities. *J. Public Econ.* **95**, 334–343 (2011).
77. Eckel, C. C., Grossman, P. J. & Johnston, R. M. An experimental test of the crowding out hypothesis. *J. Public Econ.* **89**, 1543–1560 (2005).
78. Andreoni, J., Payne, A. & Smith, S. Do grants to charities crowd out other income? Evidence from the UK. *J. Public Econ.* **114**, 75–86 (2014).
79. Goldstein, N. J., Cialdini, R. B. & Griskevicius, V. A room with a viewpoint: using social norms to motivate environmental conservation in hotels. *J. Consum. Res.* **35**, 472–482 (2008).
80. Nolan, J. M., Schultz, P. W., Cialdini, R. B., Goldstein, N. J. & Griskevicius, V. Normative social influence is underdetected. *Personal. Soc. Psychol. Bull.* **34**, 913–923 (2008).
81. Pruckner, G. J. & Sausgruber, R. Honesty on the streets: a field study on newspaper purchasing. *J. Eur. Econ. Assoc.* **11**, 661–679 (2013).
82. Harbaugh, W. T. What do donations buy? A model of philanthropy based on prestige and warm glow. *J. Public Econ.* **67**, 269–284 (1998).
83. Andreoni, J. & Petrie, R. Public goods experiments without confidentiality: a glimpse into fund-raising. *J. Public Econ.* **88**, 1605–1623 (2004).
84. Ariely, D., Bracha, A. & Meier, S. Doing good or doing well? Image motivation and monetary incentives in behaving prosocially. *Am. Econ. Rev.* **99**, 544–555 (2009).
85. Lacetera, N. & Macis, M. Social image concerns and prosocial behavior: field evidence from a nonlinear incentive scheme. *J. Econ. Behav. Organ.* **76**, 225–237 (2010).
86. Karlan, D. & McConnell, M. A. Hey look at me: the effect of giving circles on giving. *J. Econ. Behav. Organ.* **106**, 402–412 (2014).
87. Morgan, J. & Sefton, M. Funding public goods with lotteries: experimental evidence. *Rev. Econ. Stud.* **67**, 785–810 (2000).
88. Landry, C. E., Lange, A., List, J. A., Price, M. K. & Rupp, N. G. Using donor gifts to drive fundraising: theory and evidence from a natural field experiment. Working Paper https://cla.auburn.edu/economics/assets/File/UsingGiftstoDriveFundraising.pdf (Univ. Georgia, 2012).
89. Sieg, H. & Zhang, J. The importance of managerial capacity in fundraising: evidence from land conservation charities. *Int. J. Ind. Organ.* **30**, 724–734 (2012).
90. Eckel, C. C., Herberich, D. H. & Meer, J. A field experiment on directed giving at a public university. *J. Behav. Exp. Econ.* **66**, 66–71 (2017).
91. Gabaix, X. & Laibson, D. Shrouded attributes, consumer myopia, and information suppression in competitive markets. *Q. J. Econ.* **121**, 505–540 (2006).
92. Gabaix, X. A sparsity-based model of bounded rationality. *Q. J. Econ.* **129**, 1661–1710 (2014).

93. Levitt, S. D. & List, J. A. What do laboratory experiments measuring social preferences reveal about the real world. *J. Econ. Perspect.* **21**, 153–174 (2007).
94. List, J. A. Young Selfish and male: field evidence of social preferences. *Econ. J.* **114**, 121–149 (2004).
95. DellaVigna, S., List, J. A., Malmendier, U. & Rao, G. The importance of being marginal: gender differences in generosity. *Am. Econ. Rev.* **103**, 586–590 (2013).
96. Bernedo, M., Ferraro, P. J. & Price, M. The persistent impacts of norm-based messaging and their implications for water conservation. *J. Consum. Policy* **37**, 437–452 (2014).
97. Meer, J. The habit of giving. *Econ. Inq.* **51**, 2002–2017 (2013).
98. Deck, C. & Murphy, J. J. Donors change both their level and pattern of giving in response to contests among charities. *Eur. Econ. Rev.* **112**, 91–106 (2019).
99. Filiz-Ozbay, E. & Uler, N. Demand for giving to multiple charities: an experimental study. *J. Eur. Econ. Assoc.* **17**, 725–753 (2019).
100. Lee, S. & Feeley, T. H. The identifiable victim effect: a meta-analytic review. *Soc. Influ.* **11**, 199–215 (2016).
101. List, J. A. Non est disputandum de generalizability? A glimpse into the external validity trial. NBER Working Paper 27535 https://www.nber.org/papers/w27535 (National Bureau of Economic Research, 2020).
102. Harrison, G. W. & List, J. A. Field experiments. *J. Econ. Lit.* **42**, 1009–1055 (2004).
103. Henrich, J., Heine, S. J. & Norenzayan, A. Most people are not WEIRD. *Nature* **466**, 29 (2010).

Acknowledgements

The authors thank J. Andreoni and D. Wood along with seminar participants at Boston University, Chapman University and the University of California San Diego, the 2014 Science of Philanthropy Initiative meetings and the 2015 meetings of the Allied Social Sciences Association for comments that greatly influenced this manuscript. The authors thank J. Holz and F. Rundhammer for excellent research assistance, and in particular H. Beatty at Pick.Click.Give.; N. Kemppel, J. Lavoie and K. St. John at the Alaska Community Foundation; I. Dutton and D. Kaplan at the Rasmuson Foundation for their enthusiasm and support for this project; and the Alaska PFD for providing the data. Financial support for this project was provided to J.J.M. by the Rasmuson Foundation and to J.A.L. and M.K.P. by the John Templeton Foundation (award # 38909) through the Science of Philanthropy Initiative. M.K.P. acknowledges the National Science Foundation for financial support under grant award #1658743 'Using Field Experiments and Naturally Occurring Data to Understand How State Policies Impact Charitable Giving'. The funders had no role in study design, data collection and analysis, decision to publish or preparation of the manuscript.

Author contributions

J.A.L., J.J.M. and M.K.P. conceived, designed and implemented the study. J.J.M. coordinated with the State of Alaska PFD for data access. A.G.J. analysed the data. J.A.L., J.J.M., M.K.P. and A.G.J. wrote the manuscript.

Competing interests

The authors declare no competing financial interests.

Additional information

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s41562-021-01095-8.

Correspondence and requests for materials should be addressed to J.J.M.

Peer review information *Nature Human Behaviour* thanks Ann-Kathrin Koessler, Jonathan Meer and the other, anonymous, reviewer(s) for their contribution to the peer review of this work.

Reprints and permissions information is available at www.nature.com/reprints.

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

nature research

Corresponding author(s): James J. Murphy

Last updated by author(s): Feb 1, 2021

Reporting Summary

Nature Research wishes to improve the reproducibility of the work that we publish. This form provides structure for consistency and transparency in reporting. For further information on Nature Research policies, see our Editorial Policies and the Editorial Policy Checklist.

Statistics

For all statistical analyses, confirm that the following items are present in the figure legend, table legend, main text, or Methods section.

n/a	Confirmed	
☐	☒	The exact sample size (*n*) for each experimental group/condition, given as a discrete number and unit of measurement
☐	☒	A statement on whether measurements were taken from distinct samples or whether the same sample was measured repeatedly
☐	☒	The statistical test(s) used AND whether they are one- or two-sided *Only common tests should be described solely by name; describe more complex techniques in the Methods section.*
☐	☒	A description of all covariates tested
☐	☒	A description of any assumptions or corrections, such as tests of normality and adjustment for multiple comparisons
☐	☒	A full description of the statistical parameters including central tendency (e.g. means) or other basic estimates (e.g. regression coefficient) AND variation (e.g. standard deviation) or associated estimates of uncertainty (e.g. confidence intervals)
☐	☒	For null hypothesis testing, the test statistic (e.g. *F*, *t*, *r*) with confidence intervals, effect sizes, degrees of freedom and *P* value noted *Give P values as exact values whenever suitable.*
☒	☐	For Bayesian analysis, information on the choice of priors and Markov chain Monte Carlo settings
☒	☐	For hierarchical and complex designs, identification of the appropriate level for tests and full reporting of outcomes
☐	☒	Estimates of effect sizes (e.g. Cohen's *d*, Pearson's *r*), indicating how they were calculated

Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	Data was collected by the Alaska Permanent Fund Division as part of the annual PFD registration process.
Data analysis	Data was analyzed using Stata MP 16

For manuscripts utilizing custom algorithms or software that are central to the research but not yet described in published literature, software must be made available to editors and reviewers. We strongly encourage code deposition in a community repository (e.g. GitHub). See the Nature Research guidelines for submitting code & software for further information.

Data

Policy information about availability of data

All manuscripts must include a data availability statement. This statement should provide the following information, where applicable:

- Accession codes, unique identifiers, or web links for publicly available datasets
- A list of figures that have associated raw data
- A description of any restrictions on data availability

All data and statistical code are available at https://osf.io/ycafq/

Field-specific reporting

Please select the one below that is the best fit for your research. If you are not sure, read the appropriate sections before making your selection.

☐ Life sciences ☒ Behavioural & social sciences ☐ Ecological, evolutionary & environmental sciences

For a reference copy of the document with all sections, see nature.com/documents/nr-reporting-summary-flat.pdf

Behavioural & social sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	This is a quantitative experimental study. It is a natural field experiment in which individuals can voluntarily donate a portion of the annual Permanent Fund Dividend (PFD) to charity.
Research sample	The research sample is the entire population of Alaskan residents who were eligible for a Permanent Fund Dividend and applied online (the program that facilitates donations only operates with online registrations)
Sampling strategy	Randomization was at the zip-code level because state privacy laws prohibited releasing address information. A total of 540,124 individuals were randomly assigned to one of three treatments (including a control) based upon the zip code in which they lived.
Data collection	Individual were not aware they were participating in a study. The normal registration process for the annual PFD includes an option to donate some of the dividend to charity. The state's Permanent Fund Division released the PFD registration and donation data to us for this study.
Timing	Annual PFD registration began 1/1/2014. PFD registration ended 3/31/2014, but individuals could update their donation decision thru 8/31/2014.
Data exclusions	We excluded individuals were not eligible for the charity donation program, either because (a) they registered for a PFD but were not eligible for PFD or (b) applied by mail and therefore not able to participate in the charity donation program. This exclusion was pre-determined.
Non-participation	All individuals who were eligible to participate are included.
Randomization	People were randomly assigned to treatments based on their home zip code.

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

Materials & experimental systems

n/a	Involved in the study
☒	☐ Antibodies
☒	☐ Eukaryotic cell lines
☒	☐ Palaeontology and archaeology
☒	☐ Animals and other organisms
☐	☒ Human research participants
☒	☐ Clinical data
☒	☐ Dual use research of concern

Methods

n/a	Involved in the study
☒	☐ ChIP-seq
☒	☐ Flow cytometry
☒	☐ MRI-based neuroimaging

Human research participants

Policy information about studies involving human research participants

Population characteristics	All Alaskans who registered online for a PFD
Recruitment	All individuals who registered for a PFD online (and were eligible to receive a PFD) were included.
Ethics oversight	The protocol was reviewed and determined to be exempt by the University of Alaska Anchorage Institutional Review Board.

Note that full information on the approval of the study protocol must also be provided in the manuscript.