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# DO SYMPATHY BIASES INDUCE CHARITABLE GIVING? THE EFFECTS OF ADVERTISING CONTENT

By

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# Do Sympathy Biases Induce Charitable Giving?
# The Effects of Advertising Content

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November 2015
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# Do Sympathy Biases Induce Charitable Giving?
# The Effects of Advertising Content

## Abstract

We randomize advertising content motivated by the psychology literature on sympathy generation and framing effects in mailings to about 185,000 prospective *new* donors in India. We find significant impact on the number of donors and amounts donated consistent with sympathy biases such as the "identifiable victim," "in-group" and "reference dependence." A monthly reframing of the ask amount increases donors and amount donated relative to daily reframing. A second field experiment targeted to *past* donors, finds that the effect of sympathy bias on giving is smaller in percentage terms but statistically and economically highly significant in terms of the magnitude of additional dollars raised. Methodologically, the paper complements the work of behavioral scholars by adopting an empirical researchers' lens of measuring *relative* effect sizes and economic relevance of multiple behavioral theoretical constructs in the sympathy bias and charity domain within one field setting. Beyond the benefit of conceptual replications, the effect sizes provide guidance to managers on which behavioral theories are most managerially and economically relevant when developing advertising content.

**Key Words**: Charitable Giving, Sympathy Biases, Identified Victim Effect, Non-profit marketing, Advertising, Behavioral Economics, Conceptual Replications

JEL Codes: L31, M37, M31, C99

# 1 Introduction

As charities face increasingly competitive fundraising environments, they have begun to employ marketing activities to encourage donations. This has led to an explosive growth of research in recent years on the "demand side" of charitable giving. These papers have focused on various dimensions of charitable giving appeals such as incentives, seed money and match rates (e.g., List and Lucking-Reily 2002, Karlan and List 2007), social comparison (e.g., Shang and Croson 2009) and social pressure (DellaVigna et al. 2012) on donor behavior. While there is a large volume of behavioral research in the laboratory on the how advertising content affects outcomes of interest, there is little field based empirical research in general on the effects of advertising content on consumer purchases in general and donation behavior in particular. Our goal in this paper is to document and quantify the relative magnitudes of various types of advertising appeals on donation behavior motivated by the psychology theories through large scale field experiments.

Academic research by empirical scholars on advertising effects using field data typically focus on estimating the relationship between the volume, frequency and timing of advertising on market outcomes such as sales and market shares;[1] but field research on how different elements of advertising content affects market outcomes is rare.[2] Some exceptions include Bertrand et al. (2010), who vary advertising content in combination with interest rates and offer deadlines to study its impact on loan take-up in a direct mail field experiment in South Africa and Liaukonyte (2012) who codes the video content of TV ads for comparative and self-promotional advertising and studies the differential effect of demand for OTC analgesics in the US. The paucity of research on advertising content effects is partly because unlike the data on the level of spend, frequency and timing which are easily quantifiable and amenable to empirical testing, content of ads vary on a large number of dimensions, and it is difficult to isolate dimensions of interest systematically from advertisements used in the field.

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[1] See Kaul and Wittink (1995), Wind and Sharp (2009), Dellavigna and Gentzkow (2010) and Sethuraman et al. (2011) for reviews of the empirical evidence on advertising.

[2] Otherwise, research on advertising content has focused primarily on laboratory experiments. To be sure, advertising agencies and direct marketing firms routinely do copy testing before launching advertisements or sending mailers, but these studies are seldom designed to enable generalizable learning because they are built on context specific intuition; few results have been reported in the literature (e.g., Stone and Jacobs 2008).

Psychologists have found that emotions sometimes work better to motivate people to action than cognition; hence treatments that generate an emotional response can be more effective in generating donations. Sympathy is the particular emotional response triggered by another person's misfortune; laboratory experiments consistently show that evoking sympathy leads to prosocial behavior and charitable giving (e.g., Bagozzi and Moore 1994; Batson et al. 1997; Coke, Batson, and McDavis 1978).

Researchers have demonstrated framing effects called "sympathy biases" that can generate disproportionately greater sympathy relative to the actual needs of the victims. We believe this should translate to greater giving. Hence we consider three such sympathy biases to generate three advertising content treatments in our experiment. They are: (1) the identified victim effect (2) the in-group effect, (3) reference dependent sympathy effect. Sympathy can be increased by reducing the perceived social distance from the victim (Small 2011). The identified victim effect reduces the perceived social distance between donor and the victim by identifying an individual victim to a potential donor; while the in-group effect reduces social social distance as the victim is from the same in-group as the target donor. The reference dependent sympathy effect arises because sympathy is greater if one framed a victim's current condition as a decline from a reference condition, rather than simply presenting the actual condition. (Small 2010).

Our fourth experimental treatment for advertising content involves a temporal reframing of the donation. Charities often reframe an aggregate annual donation into smaller monthly or daily amount, even though the donation itself is annual. For example, a \$365 donation can be made to appear more affordable by reframing it as \$1 a day or \$30 a month. Such strategies are used also in other marketing contexts, ranging from insurance, magazine subscriptions, durable goods and charitable donations. Gourville (1998) dubbed such temporal reframing into a small daily amount as "a pennies a day" (PAD) strategy. However, the pennies a day framing violates an alternative prescription based on prospect theory that one should "integrate" losses by combining them into a larger amount (e.g., Thaler 1985). Thus far, there has been little research on the bounds of the PAD strategy and whether alternative temporal framing could lead to superior outcomes. We therefore compare donations from monthly and daily reframing.

We test these hypotheses using two field experiments in an entirely natural setting in partnership with HelpAge India, one of India's leading charities in the aid of seniors. In the first and primary experiment, we tagged on to an annual new donor acquisition campaign, where the organization sends out mailers to a cold list of around 200,000 high net worth individuals all over India. We added an additional flyer to the regular ask used in this campaign. This flyer randomized the contents of the ask message in line with the hypotheses we sought to test. The magnitude of donations solicited and obtained is significant relative to incomes in India.[3] We find economically large and statistically significant effects on both the intensive and extensive margin for the various sympathy generation and framing effects that we tested. For the various effects we test, the number of donations per mailer increases by 43%-155%, while donation amount per mailer increases by 33%-110%.

It is likely that the impact of framing on sympathy and donation is very high for a cold list of donors, because their baseline level of sympathy for the cause is likely lower. Would such effects of framing vanish among past donors, where baseline sympathy level for the cause is already high? To test this, our second experiment targeted a warm list of about 100,000 donors, who have previously donated to HelpAge. As HelpAge was reluctant to conduct the full battery of treatments, many of which had been shown to be ineffective in the first experiment, we only experimented with a few treatments to test our conjecture that the effect vanishes for past donors. As expected, the percentage impact on donations for our previously largest effect falls; the effect falls from 110% to 15%. However the effects remain both statistically and economically significant. In particular, since the baseline amount of donations from past donors is significantly higher, even the 15% increase due to the sympathy bias generates more in dollars than the 110% treatment effect on the cold list. We conclude that while framing effects of advertising content have much larger proportional impact in new donor acquisition, the economic impact in incremental absolute amounts is very significant among both new and existing donors.

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[3] According to the mail list provider, the average annual income of the households in the mailed list is about ₹600,000 (about $10,000). The donation requested is ₹9000, about 1.5% of the annual income. The median amount donated is ₹3,000, about 0.5% of the annual income.

Methodologically, this paper is part of a small but growing empirical literature in marketing using field experiments to measure advertising effects (e.g., Eastlack and Rao 1989; Lodish et al. 1995; and Sahni 2015). More broadly, this paper contributes to a research paradigm bridging empirical work in behavioral and quantitative marketing. Behavioral marketing scholars test and provide evidence for particular psychological theories in controlled laboratory settings. As the focus is often on isolating and understanding the mechanism underlying the *novel* psychological theories, there is limited interest on whether these effects replicate in field settings and whether the magnitude of the effects are managerially important. Lynch et al. (2015) describe the value of conceptual replications and replications with extensions (moderators) in behavioral work in generating marketing knowledge. Further from a managerial perspective, there is value in knowing the *relative* magnitudes of the behavioral levers suggested by different theories, so that a firm can prioritize on which behavioral lever to use. Quantitative scholars routinely focus on relative elasticities of alternative marketing actions on an outcome of interest using field data to aid managers choose the most effective marketing actions. In a similar vein, this paper complements and builds on the behavioral literature to measure the relative magnitudes of alternative behavioral levers on outcomes of managerial interest—in this case donation behavior.

The rest of the article organized as follows: Section 2 provides industry background and overviews of the literature. Section 3 describes the hypotheses, while Section 4 describes the experimental setting and treatments. Section 5 describes the results and Section 6 concludes.

## 2 Background

### A. Advertising

The advertising industry is a major sector in the world economy. In 2011, advertising spending was about $147 billion in the U.S. and $490 billion worldwide. These numbers are likely to rapidly grow as advertising is growing rapidly at double-digit rates in emerging markets such as China and India, and now accounts for a significant and growing fraction of the economy.[4] Even though a large fraction of that cost is incurred on media spending to deliver the message, the effort and cost on the development of the advertising "creative" to maximize advertising effectiveness is substantial.[5] The industry also spends considerable effort in evaluating and recognizing the effectiveness of creative advertising ideas through high profile annual awards such as the CLIO and Effie awards.

Despite the recognition that advertising content and creativity are critical to advertising effectiveness, econometric research has mostly been about the link between advertising spending on sales (see reviews of the literature in Kaul and Wittink 1995; Chandy et al. 2001). There have also been studies in the direct marketing literature about how varying the number of advertisements or frequency of mailings impact consumer purchases (e.g., Anderson and Simester 2004; Gonul and Shi 1998). This focus on spend, timing and frequency of advertising on sales in econometric modeling perhaps arises from the easy quantifiability of such variables. Liaukonyte (2012) is an exception in that she codes the video content of over 4000 TV advertisements to distinguish between comparative and self-promotional advertising and studies the impact on demand in the US OTC analgesics market.

Research related to advertising content has generally been done by consumer psychologists who have shown systematic effects of advertising content on cognition, affect and purchase intentions in the laboratory. However there has been little effort on replicating these effects in field settings (Chandy et al. 2001); further, we do not know whether the effects are large enough to be economically important.[6] We note that many advertising agencies do test alternative advertising concepts for effectiveness in on-field testing but the insights from such concept tests are hard to generalize because they do not vary content systematically in a theoretically grounded manner.[7] Bertrand et al. (2010) test the effectiveness of a of number of non-informative advertising cues and prices on loan uptake from a credit card lender using a direct mailer based randomized field experiment. Our work is similar in its focus on understanding relative magnitudes of different advertising content effects. In terms of contrasts (apart from the obvious difference in empirical contexts), their focus is on testing the economic magnitudes of ad content relative to price effects, while we test the relative magnitudes of a set of well-recognized sympathy biases documented in the psychology literature to measure the relative economic importance of these theories for managers in inducing sympathy and charitable giving.

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[4] China's advertising spend in 2011 is estimated to be $54 billion and forecast to be $64 billion, an annual growth of 16.9%. Overall, the Asia Pacific region had advertising spend of $175 billion with annual growth of 10.2%. See Group M report (http://www.aaaa.org/news/agency/Pages/120511_groupm_forecast.aspx).

[5] The industry had traditionally bundled its creative and media services and hence share of spend on creative is not available. (See Silk and Berndt 2003)

Our paper is also related to the literature on field experiments in advertising. In a landmark set of field experiments, Eastlack and Rao (1989) report the effects of a number of treatments: marketing budgets, media type and mix, creative copy, and target audience on factory shipments of various products at the Campbell Soup Company. Lodish et al. (1995) report a meta-analysis of advertising experiments using split cable, where the only difference between the experimental and treatment group was on the TV advertisements they saw. Sahni (2015) use online field experiment to test for alternative mechanisms by which the temporal spacing of advertising impacts sales; while Bart et al. (2014) use field experiments to study for which types of products mobile display advertising favorably impacted attitudes and purchase intentions.

### B. Charitable Giving

Charitable giving constitutes a significant portion of the GDP of countries. Americans gave more than $306 billion to charity in 2007, or approximately 2.2% of gross domestic product

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[6] Levitt and List (2007) provide many reasons for why the laboratory findings need to be validated on the field.

[7] Goldfarb and Tucker (2011) recently study how matching advertising to web content and the level of obtrusiveness impact purchase intent through data from a large scale field experiment.

(AAFRC Trust for Philanthropy 2008). Despite the recession, Americans gave more than $290 billion to charity in 2010, a growth of 3.8% from 2009 (AAFRC Trust for Philanthropy 2010). Individual giving accounted for 73% of this total, while foundations accounted for 14%, bequests for 8%, and corporations for 5%. Almost 70% of U.S. households report giving to charity. Even though the volume of giving is large, inter-charity competition for donations is substantial with over 800,000 charitable organizations in the United States alone. Increasingly, non-profit organizations are adopting marketing and targeted advertising techniques used by the for-profit sector to obtain funds for their causes. Watson (2006) estimated marketing spend at large U.S. non-profits at $7.6 billion based on IRS exemption data.

Despite the larger need for charitable giving in developing countries, individual giving constitutes an insignificant share in these countries. For example, even though India's giving totaled close to $5 billion in 2006 (about 0.6 percent of India's GDP),[8] individual and corporate donations constitute only 10% of charitable giving, with over 90% of the sector funded by government and foreign organizations. In fact, nearly 65 percent of the sector funds come from India's central and state governments with a focus on disaster relief. Given the massive inequalities and the enormous needs of the poor and disadvantaged in emerging economies, the ability to understand the persuasive impact of communication to increase individual giving is of great social importance.

Relative to research focused on demand for goods that improve one's own welfare, there is limited research on "demand" for spending on others' welfare (Bendapudi at al. 1996; Andreoni 2006). The field of charitable giving in economics has recently seen a surge in the use of randomized field experiments (see List 2011 for a survey), but most studies are focused on price and incentive effects on charitable giving (e.g., List and Lucking-Reiley 2002). In the context of blood donations, Lacetera et al. (2011) show that economic rewards increase blood donations and change their timing of donations; but they also find that a surprise reward for donations reduce future donations, relative to giving no reward. Academics have rarely used randomized field experiments to study the persuasive effects of advertising content in natural settings. Other behavioral work on charitable giving include: Soetevent (2005) and, who shows that revealing the identity of givers increasing donations suggesting social effects. Landry et al. (2006) find that lotteries increase giving, but surprisingly the attractiveness of the fund raiser is at least as important as the economic incentive in persuading people to give. Shang and Croson (2009) show that providing social comparisons of giving impact donation behavior. DellaVigna et al. (2012) test the role of altruism relative to social pressure in charitable giving.

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[8] Countries like Brazil and China have smaller non-profit sectors at 0.3 percent and 0.1 percent, but are growing. But this is cold comfort given the enormous needs of the poor and disadvantaged in India.

Research in laboratory settings have tested how the framing of asks impact fundraising (e.g., Ferraro et al. 2005; Gourville 1998). Fishbein's (1967) behavioral intentions model has been frequently used to model donation behavior (see LaTour and Manrai 1989). Recently Small and colleagues (e.g., Small and Lowenstein 2003, 2005; Small 2010), among others have focused on developing psychological theories that inform how generation of sympathy for other people and worthy causes affect donation behavior. We leverage on these theories for our hypotheses.

# 3 Hypotheses

Our first four hypotheses are based on framing effects from the literature on sympathy biases and the fifth is based on temporal reframing of monthly versus daily ask for an annual donation. Of the four sympathy bias hypotheses, the first three are related to how social distance impacts sympathy; the fourth addresses the sympathy bias due to reference dependence. We discuss each of the hypotheses in turn.

## *A. Identified Victim Effect*

*The death of one Russian soldier is a tragedy; the death of millions is a statistic--Joseph Stalin*
*If I look at the mass I will never act, if I look at the one I will-- Mother Teresa*

Schelling (1968) first proposed and demonstrated that an identified victim evokes greater emotion and donations than a statistical victim. As Slovic (2007) notes, people seem to care deeply about *individuals*, while numb to the sufferings of *many*. As the quotes above suggest, Mother Theresa and Joseph Stalin both seemed to have an intuitive grasp of this—perhaps the only area in which they agreed on!

There are a number of anecdotal examples related to the identified victim hypothesis. An oft-cited example is that of the child, ‘‘Baby Jessica,’’ who received over $700,000 in donations from the public, when she fell in a well near her home in Texas in 1987 and received access to a trust fund of $800,000 when she turned 25 (CBS News 2011). Donors contributed over $48,000 to save a dog stranded on a ship adrift on the Pacific Ocean near Hawaii (Song, 2002). Yet, charities struggle to raise money to feed the famished, ill and homeless --- in both developed and developing countries. In essence, when an identifiable victim is made into a cause, people appear to be more compassionate and generous; yet they give relatively little to so-called statistical victims, facing enormous needs.

Based on a dual deliberative (cognitive) and affective (emotional) process model of cognition (e.g., Chaiken and Trope, 1999; Kahneman and Frederick, 2002, Small and Lowenstein, 2005) argue that identifiable victims reduce social distance and thereby generate more sympathy because they invoke the affective (emotional) system (e.g., Small and Lowenstein 2005), while statistical victims invoke the deliberative (cognitive) system. The affective mode also dominates when the target of thought is specific, personal, and vivid as happens when we identify victims (Sherman, Beike, and Ryalls, 1999), but the deliberative mode is evoked by abstract and impersonal targets.

Some scholars have argued that the identified victim effect is plausibly due to human sensitivity to proportions rather than absolute numbers (e.g., Friedrich et al., 1999; Jenni and Loewenstein, 1997). Ten deaths concentrated in a small neighborhood of hundred people will evoke much greater consternation than ten deaths across a large city of a million people. The identified victim is an extreme example where by making the individual the cause, the reference group size is reduced to the victim. With a victim proportion of 100%, maximum sympathy is evoked. But others have shown that identification is critical, in that individuals gave more to help an identifiable victim than a statistical victim, even when controlling for the reference group (e.g., Small and Loewenstein 2003) and Kogut and Ritov 2005a). Kogut and Ritov (2005b) found that a single, identified victim (identified by a name and face) elicited greater emotional distress and more donations than a group of identified victims and more than both a single and group of unidentified victims.

In this paper, we specifically test the hypothesis that a single identified victim generates more donors and donations, relative to a group of unidentified victims.

### *B. The In-group versus Out-Group Effect*

The in-group effect suggests that potential donors are likely more sympathetic and give more to victims who share similarities with them because of reduced perceived social distance. The literature on social identity provides the foundation for the argument. Social identity is commonly defined as a person's sense of self-derived from perceived membership in social groups. Tajfel and Turner (1979) developed the concept to understand the psychological basis for intergroup discrimination. Social identity has three major components: categorization, identification and comparison. Categorization is the process of putting people, including ourselves, into categories; for example, labeling a person as Chinese, Black, female, or lawyer are all different ways of categorization. Categorization also defines our self-image. Identification is the process by which we associate or identify ourselves with certain groups. We identify with in-groups, and do not identify with out-groups. Finally, comparison is the process by which we compare in-groups with out-groups, creating a favorable bias toward the in-group.

Overall, categorization of others as belonging to an in-group arouses feelings of greater closeness and responsibility, and augments emotional response to their misfortune through greater sympathy (Brewer and Gardner, 1996; Dovidio et al. 1997) and willingness to help (Dovidio, 1984; Dovidio et al., 1997). For example, a bystander is more likely to offer help in an emergency situation (including natural disasters) if the victim is perceived as a member of the same social category as herself (Levine et al. 2002; Levine and Thompson, 2004). Cuddy, Rock and Norton (2006) find that in the aftermath of the Katrina hurricane in the US where a majority of black victims were affected, Blacks/Latino felt more sympathy for the victims compared to whites and vice versa. Sturmer, Snyder and Omoto (2005) found that homosexual volunteers were more likely to help homosexuals with AIDS than heterosexual volunteers. Kogut and Ritov (2007) find in lab experiments that Israeli students felt more empathy for a single Israeli victim of the Tsunami. Yet, they also report higher willingness of white Jewish students to contribute to a black Jewish child of Ethiopian descent compared to a white Jewish child. The students were white and the authors argue that the higher empathy for black Jews is probably a sense of responsibility for "in-group" people who are suffering. (Chen and Li, 2009) also find in lab experiments that participants are more altruistic towards an in-group match.

We wish to note that the in-group effect does not occur only with respect to sympathy generation and charitable giving. It is also applicable in commercial advertising situations, where the goal is to persuade the target to buy a product or service for oneself. Evans (1963) showed that customers are more likely to buy insurance from a salesperson similar in age, religion, politics and even cigarette smoking habits!

In this paper, we test the hypothesis that an in-group victim generates more donors and donations, relative to an out-group victim.

### *C. Out-group "Identified Victim" versus "Unidentified" Group*

As discussed above, research has demonstrated that sympathy would be greater (1) for an in-group individual relative to an out-group individual; and (2) an identified individual victim than a group of victims. But how does an identified out-group individual fare relative to the group? To the best of our knowledge, there is no research on the strength of the identified victim effect relative to the in-group out-group effect. While we have no apriori hypothesis on which effect is stronger, we test the relative magnitudes of the effects in this paper.

### *D. Reference Dependent Sympathy*

Our final sympathy bias hypothesis is based on the "reference dependence sympathy" effect. When a major disaster happens, there is large outpouring of sympathy and substantial donations are made. Private donations averaged USD 1839 per person for Hurricane Katrina, and as much as USD37 per person for 2005 Kashmir earthquake, which was not very much covered by mass media (Spence 2006). Yet donations for AIDS victims amount to about USD 10 per victim. Yet the magnitude of the problem of AIDS, malaria, famine and unsafe water is far more substantial. Over 660,000 people die from AIDS, malaria, famine, and unsafe water per month; and that monthly number is close to double the number of lives lost as a result of the Asian Tsunami, Hurricane Katrina, and the earthquake in Kashmir.

What explains the differences in sympathy and giving behavior? Why do we feel more sympathy for those who lost their homes due the housing bust than for the chronically homeless? The literature on reference dependence based on prospect theory suggests a possible explanation. Victims of chronic conditions maintain a constant-state of welfare but victims of events have suffered a loss in welfare. People value not an absolute amount, but rather gains and losses relative to a reference point (Kahneman and Tversky, 1979). Small (2010) shows that reference dependence is not only supported in the context of one's own utility, but also applicable to sympathy generated for others. She finds that reference-dependent judgments and decisions are a function of emotional responses to *changes* in others welfare. When judgments are made toward a pallid target, the emotional mechanism ceases to exert influence; therefore, others' losses hurt more than their chronic conditions.

### *E. Temporal reframing: Monthly versus Daily Ask*

Marketers temporally reframe the amount of an annual donation into smaller monthly or daily amounts, even though donation itself is annual. Such strategies are used in a variety of contexts, ranging from insurance, magazine subscriptions, durable goods and charitable donations. A $360 annual insurance premium or donation to NPR seems more affordable when framed as less than $1 a day. Gourville (1998) dubbed such temporal reframing into a small daily amount as "a pennies a day" (PAD) strategy.

Standard economic theory would suggest that mere temporal reframing should not affect behavior. Different presentations of the same stimuli-- in this case, the same physical cash flows, should not alter donor behavior (e.g., Tversky, Sattath, and Slovic 1988). Gourville therefore proposes a two-step consumer decision-making process of (1) comparison retrieval and (2) transaction evaluation to explain why PAD strategies may be effective. He demonstrates in laboratory experiments that the PAD framing of a target transaction systematically fosters the retrieval and consideration of small ongoing expenses as the standard of comparison, whereas an aggregate framing of that same transaction fosters the retrieval and consideration of large infrequent expenses. Since most individuals indeed perform many small transactions routinely, this difference in retrieval makes it more likely that the individual will more favorably evaluate and comply with the smaller transaction.

However, prospect theory (Kahneman and Tversky 1979) and its derivative mental accounting (Thaler 1985) would predict that the PAD strategy would backfire by magnifying the perceived cost of the donation or spend. Their recommendation to "integrate small losses" is based on the idea that an individual would rather than experience many small costs, with each cost assessed at the steepest and most painful part of the prospect theory value function, prefer to experience one larger loss taking advantage of the flattening value function for increasingly larger losses.

Hence, would the $360 transaction be perceived more favorably if temporally reframed as $30 per month or less than $1 per day? This would depend on what type of small transaction would be considered more normal or less painful: ongoing monthly payments such as utility bills or rentals or daily spend such as for a cup of coffee or tea? If compliance is easier for monthly payment, where people do not have much discretion, as opposed to daily spend where there is discretion, it is possible that a monthly framing might be more effective. Such a framing has not been subject to empirical testing. We therefore do not have a strong a priori hypothesis about which framing will lead to more donors and donations; we treat this as an empirical question.

# 4 The Primary Experiment: New Donor Acquisition

### The Setting

The aged are a growing population worldwide as life expectancy increases. While there are safety nets like social security and Medicare in the developed world to support the elderly in their old age, these mechanisms are not developed in countries like India and the primary source of support for the elderly is the support from the savings of the elderly and support from the joint family. With growing economic opportunities, the young migrate from their traditional homes in villages or set up nuclear households, leaving the elderly increasingly abandoned. Worse, the aged are abused with children taking control over the aged parents' property and financial resources and then abandoning them. Given the magnitude of the problem, the Indian Government recently passed a law providing for imprisonment of children neglecting elderly parents.[9] Nevertheless, there is great need for societal support of the elderly, especially when the children do not have the means to support even themselves. India has currently 90 million elderly, of whom about over 7 million (7.8%) require some form of societal support (Rajan 2006).

HelpAge India was founded in 1978 as a secular, not-for-profit organization registered under the Societies' Registration Act of 1860 to provide relief to India's elderly through various activities. Focus areas include advocacy for elders' rights, healthcare, social protection, shelters and disaster mitigation.[10] Our investigation is around one HelpAge social protection program called "Support a Gran." In this program, elderly destitutes are adopted by HelpAge and provided with basic food, minimal clothing and necessities and a small amount of discretionary cash on a monthly basis. The "Support a Gran" donations are considered "restricted gifts" in that funds raised for this program can only be used for this program.

Our experiment on behalf of "Support a Gran" was done around an annual fundraising campaign of HelpAge in March 2011. This fundraising campaign coincides with the Hindu festival of Holi in March, a period of celebration of the triumph of good over evil, and considered a time for doing good and giving. It is also fortuitously close to the annual tax filing deadline of March 31, which perhaps serves as another incentive to "give." The appeals are targeted to a "cold" mailing list of 184396 high net worth individuals in India in order to acquire new donors.

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[9] The laws are similar in spirit to laws in developed world designed to prevent neglect of children.

[10] HelpAge India Brochure accessed March 1, 2012 from website http://www.helpageindia.org/pdf/ Organizational-Brochure.pdf

Appeals to cold mailing lists tend to have very low response rates; typical response rates at HelpAge have been around 0.1%. With giving per donor averaging around ₹3000,[11] the low response rates of about 0.1%, implies that actual money raised per mailing is only around ₹3. With costs of the campaign averaging around ₹6 per mailing, the campaign is considered as a loss-leader to acquire new donors with propensity to donate, who can be more efficiently reached in subsequent mailings to "active" (hot) donor lists or "dormant" (warm) donor lists. In standard marketing parlance, this campaign is part of the acquisition cost of new donors that is worth only because there is a lifetime value for each acquired donor through subsequent donations. Our experiment imposed little incremental cost to HelpAge, except the insignificant cost of printing a small color flyer and including it in addition to the standard one page appeal sheet.

### Experimental Treatments

As described earlier, we test hypotheses related to the following four psychological effects: (1) identified victim (2) in-group versus out-group victim (3) reference dependence sympathy and (4) temporal reframing--daily versus monthly ask. We provide the copy of the flyer we used in one condition (Individual-Ingroup-Loss-Monthly) below.

We explain how the flyer was modified for other 11 treatment conditions. We operationalize the test of the identified victim effect using two different types of treatments: an individual (I) and group (G) condition. See stylized examples of the individual and group condition below. The areas marked in bold are the text which change for different conditions (apart from appropriate change of pronouns and names in the rest of the text).

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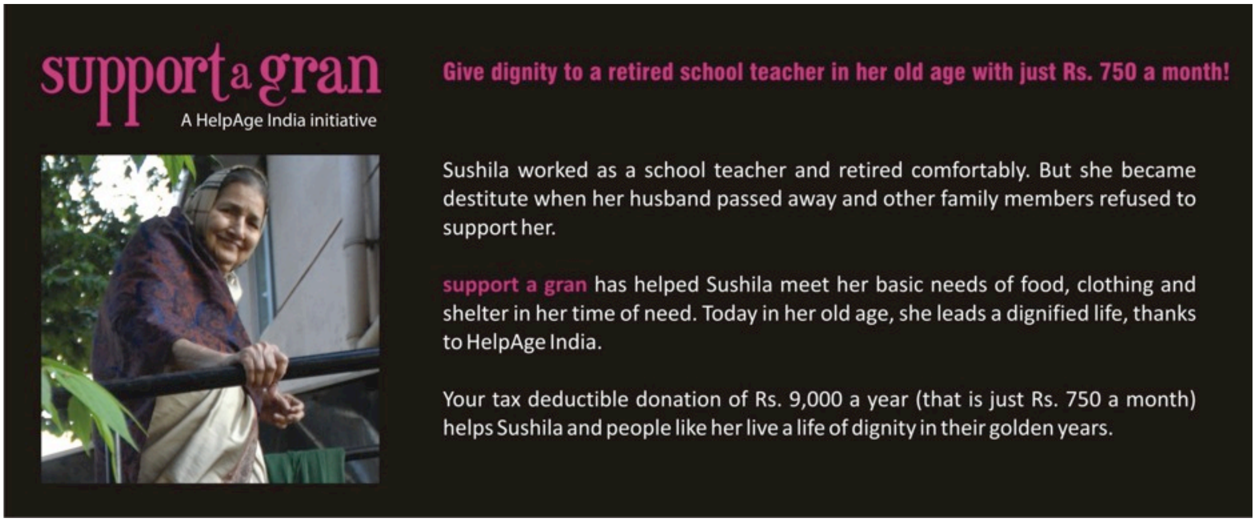
[11] The exchange rate in May 2011 averaged ₹44.93 (Indian Rupees) for $1 (U.S. Dollar). (www.xrate.com)



support a gran

A HelpAge India initiative

**Give dignity to a retired school teacher in her old age with just Rs. 750 a month!**

Sushila worked as a school teacher and retired comfortably. But she became destitute when her husband passed away and other family members refused to support her.

support a gran has helped Sushila meet her basic needs of food, clothing and shelter in her time of need. Today in her old age, she leads a dignified life, thanks to HelpAge India.

Your tax deductible donation of Rs. 9,000 a year (that is just Rs. 750 a month) helps Sushila and people like her live a life of dignity in their golden years.

In the individual condition, we describe an identified individual (Sushila in the example) along with her photograph, while in the group condition we describe the victims as group of four women (who are shown in a picture collage) and describe the group.[12] We implement the in-group and out-group treatment as sub-treatments within the individual condition: As Hindus are the overwhelmingly majority community in India and Christians form a very small minority, we use a Hindu woman (Sushila) for the in-group treatment. For the out-group treatment, we use a Christian woman belonging to the Anglo-Indian community (Shirley Barrett). The individuals pictured had to be real beneficiaries with real stories of the non-profit as per the ethical guidelines of the organization. We could not therefore merely change the names of the beneficiaries with the same image. We discuss a subsequent robustness check using an M-Turk experiment to rule out if the attitude to the charity changed due to differences in the images in the in-group-outgroup condition among Hindu respondents.

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[12] While the individual treatment uses a Hindu and Christian woman as victim (the religion is not mentioned, but can be inferred from their names), the group treatment simply describes a group of four women, without mentioning religion. While we could have mentioned they were Hindu or Christian even in the group condition and obtained a fully crossed design, HelpAge did not consider it appropriate to mention religion in the flyer. Further not mentioning religion in the group condition made it in some ways more comparable to the individual treatment where religion is not mentioned, but only (potentially) inferred by the reader from the name.

**Individual Condition**

| | |
|---|---|
| **Photo of Sushila** | **Sushila worked as a school teacher and retired comfortably**. But she became destitute when her husband passed away and other family members refused to support her.<br>Support a Gran has helped Sushila_meet her basic needs of food, clothing and shelter in her time of need. Today in her seventies, she leads a dignified life.<br>Your tax deductible donation of ₹9000 a year (that is just **₹750 a month**) helps Sushila and people like her live a life of dignity in their golden years. |

**Group Condition**

| | |
|---|---|
| **Photo Collage of four unnamed ladies** | **These ladies share a common story. They worked as school teachers and retired comfortably.** But then they became destitute when their husbands passed away and other family members refused to support them.<br>Support a Gran has helped them all meet their basic needs of food, clothing and shelter in their time of need. Today in their seventies, they lead a dignified life.<br>Your tax deductible donation of ₹9000 a year (that is just **₹750 a month**) helps these and other people like them a life of dignity in their golden years. |

We implement the reference dependent sympathy treatment as follows. For the loss condition, we highlight the fact that the individual concerned had lived an independent life earlier as a school teacher and retired, before she became destitute. In a lab experiment, to create the contrasting chronic treatment, we could have stated that “Sushila has led a life of deprivation all her life.” However, as this was a natural field experiment, HelpAge policy would not allow for any kind of deception or falsehood in messaging. Hence we chose an "uncertain" reference treatment, where we omit mentioning about her past life. So we dropped the first line: "Sushila worked as a school teacher and retired comfortably." The uncertain treatment started with the following sentence: “Sushila became destitute when her husband passed away…” Similarly, the group treatment also dropped the reference to the past and simply said: “These ladies share a common story. They became destitute, when their husbands passed away…”

We implement the monthly-daily temporal reframing treatment as follows. While everyone is given an amount of ₹9000 to anchor as the amount needed to support one person over a year, that same amount is framed as ₹750 a month for the monthly condition and ₹25 a day for the daily condition.[13]

In the control condition, HelpAge sends its routine flyer—a one page sheet requesting for donation. In each of the treatment conditions, in addition to the routine flyer, an additional one page flyer—described above was sent. All of the flyers are presented in the online appendix.

### Experimental Design

Within the individual treatment, we follow a full factorial design on the in-group-out-group, reference dependence (loss/uncertain) and temporal reframing (monthly/daily) ask conditions. Thus we have 2×2×2=8 conditions in the individual treatments. As we explained earlier, within the group treatment, we do not providing any identifying characteristics including religion—hence we do not have an in-group and out-group condition in the group treatment. So we only have the remaining 2×2=4 conditions within the group treatment. Finally, we have a control condition, where we do not send the additional flyer at all; this is what HelpAge would have done in the absence of our experiment. Thus in all, we have 8+4+1=13 treatment conditions.

The full set of treatments is listed in Table 1. The mnemonics provided will serve to identify treatments in a meaningful manner.

*** Insert Table 1 here***

We randomly assign names on the mailing list roughly equally to 12 treatments and leave a slightly larger number of names for the control treatment. The exact number of mailings for each treatment is reported in Table 2 along with the descriptive statistics.[14]

*** Insert Table 2 here***

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[13] As a price reference, a regular cup of coffee at India's largest coffee chain Café Coffee Day costs ₹40. In that sense, it satisfies the "pennies a day" logic of a routine and ongoing daily expense.

[14] To assess the effectiveness of the randomization, we check whether the number of mailings is roughly equal across the main observable we have in the mailing list: the different states of India. Indeed the assignments are roughly equal for all treatments at the level of each state.

# 5 Results

### Summary Statistics

We report summary statistics associated with each of the treatment cells in Table 2. Roughly 14000 people were assigned to each treatment condition, while about 15,500 were assigned to the control condition. We report three outcome metrics for each treatment: (1) donation rate, i.e., % of mailings that generated a donation; (2) donation amount per mailing (₹/mail); and (3) donation amount per donor (₹/donor), i.e., donation amount, conditional on giving.

The highest donation rate and ₹/mail is for the Individual-In-group (Hindu)-Loss-Monthly (IHLM) condition. This condition generated 3.3 (0.36/0.11) times the donation rate as the control condition. Further the ₹/mail in this condition is 3.78 (16.28/4.30) times the amount generated in the control condition. In contrast, the worst performing Group-Loss-Daily (G_LD) condition produced only 59% of donors and raised only 60% of ₹/mail relative to the control. In general, the group mailer is not only ineffective, but in combination with the daily ask framing performs substantially worse than the control condition. Overall, these results suggest that relatively minor variations in advertising content significantly affect persuasion and charitable giving.

### Tests of Hypotheses

We test our hypotheses about the persuasive effects of alternative treatments by comparing (1) the donation rate and (2) ₹/mail across the relevant treatments. An additional question is when there is an increase in ₹/mail, whether it is only due to a higher donation rate or whether individuals who donate also feel more sympathy and give more. For this, one cannot simply compare ₹/donor, i.e., donation, conditional on giving, because when the more effective treatment generates more donors, the marginal donors are innately less interested in the cause and are therefore likely to give less. To make an apples-to-apples comparison, we can rank the donors in descending order of their donations within each treatment and do a paired test of donation amounts for a donor of given rank.[15] The logic is that if treatment A generates more sympathy, a donor of a given rank subject to treatment A should give more relative to an identically ranked donor subject to treatment B.[16]

### *A. Identified Victim Effect*

Figure 1 shows the results for the identified victim effect. Panel A compares the donation rates across the individual and group conditions. The average donation rate in the individual condition is 0.24%, while it is only 0.09% for the group condition and the difference is significant ($p<0.05$). Thus the donation rate for the individual treatment is 2.55 times the donation rate in the group treatments.

Panel B compares the ₹/mail. Not only is the donation rate higher in the individual condition the donations raised per mailing is also higher. While, the average donation per mailing is ₹8.83 in the individual condition, it is only ₹4.20 in the group condition. This ratio of 2.1 shows that a charity more than doubles donation dollars by recognizing the identified victim sympathy bias in making its appeals.

Panel C graphs the ratio of individual to group donations of identically ranked pair of donors. There are 51 donations in the group condition and 260 donations in the individual condition. However the number of mailers in the individual condition is (roughly) double the number of mailers in the group condition. Given the percentile discussion in footnote 14, this translates to comparing the 51 ranked donations in the group condition against the top 51 *odd* ranked donations in the individual condition. All of the 51 ratios are at or above 1, suggesting that the identified victim effect not only causes more donors to give, but also increases the giving among those that give. The effect is statistically significant; the mean of the ratio is 3.6 and the 95% confidence interval of (3.05, 4.16) clearly excludes 1.

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[15] Comparing donations of persons of identical rank is valid only if we have identical number of mailings in the different comparison treatments. Otherwise, one will have to compare donors of identical percentiles rather than ranks.

[16] However there may be other possibilities for the donation decision process. As an example, the additional donors for the more effective treatment may be systematically wealthier and therefore give more, unrelated to their level of sympathy. As we do not have demographic information on the donors, we are unable to rule out this explanation by checking whether there are any systematic differences in donor demographics for the different treatments. We hope future research can address this issue. We thank a reviewer for raising this possibility.

### *B. In-Group versus Out-group Identified Victim*

Figure 2 shows the results of the tests for in-group versus out-group. From Panel A, we see that the donation rate in the in-group condition is higher at 0.28%, relative to the out-group condition at 0.19%. Thus, the number of donors increase by 42% with an in-group individual relative to the out-group individual. The difference is statistically significant at the 95% level. Note that, the average individual effect of 0.24%, reported in Figure 1 is the average of the in-group and out-group effect.

From panel B, we see that the ₹/mail is also higher at ₹11.29 for the in-group condition, relative to ₹6.38 for the out-group condition thus generating 77% more donations. Comparing the increase in donation rate of 43%, and the increase in donations of 77%, we can conclude that not only does an in-group lead more donors to give, those donors also give substantially more to in-group victims.

Panel C show that conditional on giving, identically ranked individuals in the in-group condition, give more than the donors in the out-group condition. As roughly identical number of mailers was sent in the in-group and out-group conditions, we directly compare the donations of the same rank. There are 153 in-group donations and 107 out-group donations. We therefore compare the top 107 ranks in both the conditions. Only two of the 107 pairs have ratios less than 1. The effect is statistically significant; the mean of the ratio is 2.61 and the 95% confidence interval of (2.40, 2.82) clearly excludes 1.

One concern here is that even though our potential donor base is predominantly Hindu, there are also Christian and Muslim potential donors in the sample. Even though we do not have access to the religion information of the potential donor database, the email list provider indicates that Hindus consisted of about 90% of the sample, Muslims about 7%, Christians about 2% and others about 1%. This implies that our estimates of the ingroup and out-group donation and giving rates and the differences are potentially biased. In the appendix we show mathematically that the difference in giving rates when the exact identity of the potential donor is known will be larger relative to the estimates we obtain where some of the potential donors are also from the outgroup. Thus the current estimates of the difference between in-group and outgroup giving are an underestimate. We report robustness and mechanism checks around the in-group result using a survey based experiment in Section 6.

### *C. Out-group "Identified Victim" versus "Unidentified" Group*

Figure 3 compares the out-group "identified victim" effect against the "unidentified" group. From panel A, we see that the average rate of donations in the identified out-group condition is higher at 0.19%, relative to the group condition at 0.09%, Overall, the number of donors can be increased by 110% with an out-group identified individual relative to an unidentified group, suggesting that the identified victim effect is stronger than the in-group effect in inducing sympathy and giving. The difference is clearly statistically significant ($p<0.05$).

Not only is the donation rate higher. From panel B, we see that that the identified out-group condition generates 52% more donations; ₹/mail is ₹6.38 for the out-group condition, relative to ₹4.29 for the group condition.

Roughly equal number of mailers was send to the out-group and group conditions. So we directly compare donations of a given rank. Given 107 donations from the outgroup condition, and 51 donations from the group condition, we compare the top 51 pairs of donations from each condition. Only one of 51 pairs has a lower ratio than 1. The effect is statistically significant; the mean of the ratio is 2.04 and the 95% confidence interval is (1.80, 2.28), excludes 1.

### *D. Reference Dependent Sympathy*

Figure 4 shows the tests for reference dependence sympathy by comparing the loss condition against the uncertain condition. From panel A, we see the donation rate for the loss condition is higher at 0.23%, relative to the uncertain condition at 0.15% ($p < 0.05$). Overall, the number of donors was higher by 51% in the loss condition.

Panel B shows that the ₹/mail is also higher at ₹8.37 for the loss condition, relative to ₹6.28 for the uncertain condition. Thus the loss condition generates 33% more in terms of funds raised.

Panel C also shows that conditional on giving, identically ranked individuals in the loss condition give more than the donors in the uncertain condition. We had 187 donations in the loss condition and 124 donations in the uncertain condition. Only 4 out of 124 pairs have a ratio less than 1. The mean of the ratio is 1.97 and the 95% confidence interval is (1.81, 2.14), excludes 1.

A potential alternative explanation for the greater giving in the loss condition could be that school teachers may be an in-group with respect to the donors. We note that the socioeconomic status of the potential donors is much higher than those of school teachers and therefore school teachers are an unlikely in-group for these potential donors, and possibly an out-group in terms of socioeconomic status. Nevertheless, the issue needs further exploration in future field research.

### *E. Temporal Reframing: Monthly versus Daily Ask*

Figure 5 compares outcomes for the monthly versus daily asks. From panel A, we find that that the donation rate is higher in the monthly condition at 0.24%, relative to the daily condition at 0.14%. Thus, the monthly condition increases donation rate by 71%. The effect is statistically significant ($p<0.05$).

From panel B, we see that the ₹/mail is also higher at ₹9.10 for the monthly condition, relative to ₹5.47 for the daily condition. Thus the monthly condition also leads to 66% more funds raised. Overall, in contrast to recent support for the pennies a day framing effect, we find that monthly temporal reframing actually leads to better persuasive outcomes.

Panel C demonstrates that conditional on giving, donors on average do give more in the monthly condition. We had 216 donations in the monthly condition and 115 donations in the daily condition. None of the 115 pairs have a ratio less than 1, suggesting that the monthly reframing leads to more robust and higher donations compared to daily reframing. The mean of the ratio is 3.69 and the 95% confidence interval is (3.17, 4.2), which excludes 1.

### Multivariate Regression Analysis

Thus far, we analyzed the data---one pair of treatments at a time. We now analyze the experimental data through two multivariate regressions that controls for simultaneous variations in multiple treatments: a logistic regression on donation choice and a tobit regression on donation amounts. We use a tobit regression, because donations are left censored at zero. The results are reported in Table 3.

The logistic regression results report both the coefficient estimates and the odds ratios. The individual coefficient is positive and significant ($p<0.01$). This represents the individual-outgroup condition in the regression, and shows that the individual-outgroup condition more than doubles the odds of donation (odds ratio=2.1), over the group condition. The in-group condition further increases the effectiveness of the outgroup condition relative to the group condition by about 40% (odds ratio 1.41). We note that in combination, the individual-ingroup condition increases the odds of donations three times relative to the group condition. This can also be directly checked by replacing the "individual" variable with "outgroup" variable in the logistic regression. Thus the identified victim effect is substantial; even an identified out-group victim overwhelms giving for a group of victims.

Further, the results show significant effects of reference dependence, with the loss condition increasing the odds of donations by 51% relative to the uncertain condition. Finally, temporal reframing affects donations, with monthly ask increasing the odds of donations by 71%.

The tobit regression results show that our treatments significantly affect the donation amounts. Specifically, we find that the in-group identified victim treatment (captured by the Individual+Ingroup coefficient) raises ₹4851 per donor more than the group treatment. Even the out-group identified victim raises ₹3095 more than the group treatment. Reference dependence in the form of the loss conditions generates ₹1786 more than the uncertain condition. Finally, the monthly temporal framing leads to greater giving of ₹2438 relative to a daily temporal frame. Overall these results show strong statistical and economic significance of advertising content effects.[17]

## 6 Robustness Checks

We conduct two robustness checks. The first seeks to assess the robustness of the ingroup-outgroup hypothesis. The second addresses the question that while we have demonstrated large effects of advertising content for a cold list, consistent with sympathy biases, whether such effects are likely to hold also for a warm list where people have already shown an interest in the cause.

### The In-group- Outgroup Effect Replication Using Survey based Experiments

We demonstrated in the field experiment that an ask around an in-group person (Hindu woman where the cold list is about 90% Hindu) leads to higher donation rates and donation amounts than an out-group person (Christian woman). Nevertheless, our result is open to other alternative interpretations. For example, it might be the case that Christian women may be considered to be wealthier on average and may be seen to have less "needs" and therefore may generate less donations. If indeed it is the outgroup effect driving the lower donations, it must be the case that potential Christian donors are more likely to donate to the Christian subject and less to the Hindu subject. However, given the low number of potential Christian donors this is hard to test within our field sample.

We therefore conducted a survey based experiment to assess this question. First, we conducted a survey through M-Turk on Indian respondents where we showed the same flyer as in our cold list experiment (with individual condition, loss condition and monthly condition) but one group receiving the flyer with the Hindu woman (Sushila) and the other group receiving the flyer with the Christian woman (Shirley). After reading the flyer, the respondents were asked about their likelihood of giving (1-10 scale), whether they had given in the past, their religion, education and income. Unfortunately, the respondents through M-Turk were disproportionately Hindu. Given our interest in getting additional Christian respondents, we augmented our sample through an email mailing list of Christian respondents from an Indian direct marketing company (Yellow Umbrella) and did the identical survey with these respondents, randomizing for in-group and out-group treatments.

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[17] As the group condition did not have ingroup and outgroup sub-conditions, we cannot identify an interaction effect of ingroup-outgroup with the individual condition beyond the main effects of individual and ingroup from the experimental data.. Other interactions with respect to loss or month conditions were not significant. We therefore report only the main effects. In general, logistic regressions have some level of interactions built in due to their intrinsic nonlinearity and this may explain why the loss or month interactions were not significant.

The results from the survey are reported in Table 3a-b. Table 3a provides the descriptive statistics across the four groups: (1) Hindus asked to donate for Sushila (in-group); (2) Hindus asked to donate for Shirley (outgroup) (3) Christians asked to donate for Sushila (out-group); (2) Christians asked to donate for Shirley (ingroup). Hindus say they would give more overall in the sample, though their income and educational conditions are not higher. Past giving is roughly similar across all treatments, except for Christians asked to give to Shirley. What is clear is the base rates of giving are higher for ingroups relative to outgroups for *both* Hindus and Christians. This is particularly interesting given that the past giving is much lower for Christians facing the Shirley treatment (ingroup) compared to Christians facing the Sushila treatment (outgroup).

Table 3b reports results of an OLS regression on the likelihood of giving (a 10 point scale) with controls for past giving and education to test the ingroup-outgroup effect. These results show that the ingroup effects are indeed statistically significant for both Hindus ($p<0.1$) and Christians ($p<0.05$). Not surprisingly, Past giving is overall very significant and higher levels of education lead to higher giving. Income was highly correlated with education and created multicollinearity issues, hence we dropped income from the final regression we report (education had better explanatory power). This survey-based experiment result not only replicates the ingroup effect for Hindus from the field experiment, but also supports the ingroup effect for Christians, giving us greater confidence in our in-group-out group comparison result.

Next, we explore whether the difference in giving for ingroup and outgroup is caused by differences in attitudes towards the charity rather than differences in sympathy.[18] We ran a second M-Turk experiment randomizing the ingroup and outgroup condition across Hindu respondents and asked them to rate the charity on a 10 point scale on three dimensions adapted from Webb et al (2000). The three questions are: (1) HelpAge India serves a good cause; (2) HelpAge India is a well-managed charity; (3) I have a positive image of HelpAge India.

The regression results are reported in Table 3c. For all three questions, the Sushila (ingroup) variable is insignificant, indicating no statistically difference in donor's perceptions of the charity based on the ingroup or outgroup treatments. Thus the difference in likelihood of giving does not appear to rise due to differences in how the charity is perceived based on the target recipient featured in the charity.

*** Insert Table 3a-c here***

### Raising Donations from Past Donors

Thus far, we have demonstrated that advertising content has large effects on both donation rates and amounts raised. The odds of giving increased from as low as 51% between the loss and uncertain condition tests for the reference dependence sympathy effect to as high as 300% for the in-group relative to the group condition for the identified victim effect.

We conjectured that sympathy biases may have relatively strong impact in the context of new donations, because the baseline levels of sympathy might be lower. But the effects of sympathy bias on donations may be more muted when the base levels of sympathy are higher. To test this, we decided to test if the effects of sympathy bias may be replicated among past donors, for whom the baseline sympathy for the cause must be higher. [19]

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[18] We thank a reviewer for the suggestion.

[19] Another possibility is that past experience with HelpAge has reduced the uncertainty (lower variance) about the charity; hence the framing effects may have limited impact on the warm list. Whether learning on selection accounts for

*Experimental Treatments*

HelpAge conducted multiple mailings to their warm list of past donors. One such mailing was in November 2011 around the festival of Diwali—the festival of lights---which is celebrated almost all over India. While Diwali has religious legends associated with the ascendancy of good over evil, it also coincides with the end of the Indian harvest season, and again has been associated with gift giving and charitable giving.

HelpAge was reluctant to test the entire set of previous experimental treatments on their warm list of past donors, given that the results appear to favor monthly ask, and loss condition for reference dependence. However, they were curious about understanding the boundaries around the identified victim effect. We therefore tested the individual and group treatments from the earlier experiment (with loss framing and monthly ask), where the photos and text communicated either the suffering of the individual or group. To this, we add a third treatment, where we showed a group photo, but in the text we used a story that used the example of a particular individual. The goal was to test whether the text associated with the individual evoked the identified victim sympathy bias, while the group picture communicated that this is a problem for a larger group. We show the treatment associated with the Group Photo-Individual Text condition below.

**Group Photo-Individual Text Condition**

| | |
|---|---|
| Photo Collage of four unnamed ladies | **These ladies share a common story. For example, Sushila worked as a school teacher and retired comfortably.** But then she became destitute when her husband passed away and other family members refused to support her.<br>Support a Gran has helped people like Sushila meet their basic needs of food, clothing and shelter in their time of need. Today in their seventies, they lead a dignified life.<br>Your tax deductible donation of ₹9000 a year (that is just **₹750 a month**) helps Sushila and people like her live a life of dignity in their golden years. |

*Experimental Design*

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the differences in rates of giving across the warm and cold list would be an interesting possibility for future research. We thank an anonymous reviewer for suggesting the learning explanation as a possibility.

The three treatments (as described above) and the number of mailings for the three treatments and descriptive statistics are listed in Tables 4a and 4b. We also report on the past giving of donors which are standard in the direct marketing literature such on recency (# years since past donation), frequency (#times donated in last 5 years) and monetary value of donations in the past (average value of previous donations) in each treatment; we will use them as controls in addition to the treatments in analyzing the donations. The mnemonics provided serve to identify treatments in a meaningful manner. We randomly assign names on the mailing list to the three treatments, but given that we expected the group condition to be the least effective, we sent only half the number of mailings to this condition. The exact number of mailings for each treatment is reported in Table 4b along with the descriptive statistics. As expected, the giving with this warm list average about 1.2%, about four times higher than with the cold list. The ₹ per mailing also was higher at ₹45. This validates the use of cold lists to generate donors (even at a loss) in order to be able to more efficiently raise funds in subsequent fundraisers targeted to past donors.

*** Insert Table 4 here***

*Results*

Figure 6 reports the results in terms of donation rates and ₹/mail under the three conditions. As before, we replicate the result that the individual condition (with both individual photo and text) generated more donors and higher amounts of donations relative to the group condition (with both group photo and group text). The difference in donor rates (1.33% versus 1.14%) however is smaller than with the cold list of new donors, and is significantly different only at p<.01. ₹/mail is also higher at ₹53.10 for the individual condition, relative to ₹50.7 for the group condition, an increase of 4.7%. To our surprise, we found the group photo-individual text condition generated worse outcomes than the pure group condition. Donor rates were only 0.95%, while the ₹/mail is also substantially lower at ₹37.40. We speculate that having the individual text as an example where otherwise the photo and initial introduction are about the group potentially destroys the fluency of the message, by mixing up a group story with an individual example, rather than generating a bump up in donation rates relative to the group message.

The results of the logistic and tobit regressions for donation choice and donation amounts are reported in Tables 4b and 4c respectively. Indeed the results reported under model 1 in Tables 4b and 4c are both qualitatively and quantitatively identical to the paired treatment comparison results discussed in the previous paragraph. In Model 2, we report the results of the logistic and tobit regressions, controlling for donor heterogeneity exhibited through past donation choices described earlier. The effects of the experimental treatments continue to be virtually identical in magnitude relative to the regressions without the controls, reflecting the fact that our assignment to treatments was random; at the very least this should give faith in the quality of our random assignment. In terms of substantive insights from the control variables, we find that recent and more frequent donors are not only more likely to donate, but also donate more. We see that higher monetary value of past donations has a negative impact, but only significant at $p<0.1$). While we cannot explain the negative impact, we note that even if considered significant, the economic magnitude is small. A ₹1000 increase in total past giving reduces the odds by only about 1% (odds ratio of .99), which is much smaller than the impact of other variables. However larger monetary amounts do predict greater current dollar value of donations as expected.[20]

Thus we conclude that the effects of sympathy bias affect donation behavior even among past donors, who are already sympathetic to the cause, but the framing effects are attenuated relative to the cold list setting. Given that the number of donors and the amount of money raised with the warm list is about 10 times greater, the 16% increases in donors and the 4.7% increase in the amount of money raised is comparable in economic magnitude in terms of incremental donors and money raised with new donor acquisition. Hence we conclude that effects of sympathy biases continue to remain economically significant even among warm donors.

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[20] We tested for interactions between past giving and treatment. We did not find significant interactions for donation rates. In the tobit regression on donation amount, we found negative interactions with recency and positive interactions with monetary value for the treatments.

# 7 Conclusion

This paper investigated the persuasive effects of advertising content on target outcomes, in the context of fund raising through the use of large scale field experiments. Our experimental treatments were guided by the psychological literature on sympathy biases and framing effects. Broadly, we find that even minor variations in the persuasive message have large and dramatic impact on donor behavior, both in terms of the donation rates and amounts raised. The results are particularly dramatic and stark, given that there are no differences in incentives, match rates or social pressure, which have been the focus of much previous research. Minor differences in language, lead to fairly large differences in outcomes. More specifically, our key findings are as follows:

1. Framing has large effects on donor response both in terms of donation rates and donation amounts (₹/mail). Among potential new donors, donation rates increase from as low as 51% between the two reference dependence conditions to as high as 300% for the in-group relative to the group condition. The sympathy bias and framing effects are much larger among new donors relative past donors in percentage terms, but as the giving rates are much higher among past donors, the incremental money raised in dollar terms is larger with the warm list.
2. We find significant evidence of the identified victim effect; an individually identified victim is likely to generate over two and a half times more donors and over twice the donations relative to an unidentified group of four victims.
3. When the identified victim is from an in-group (Hindu majority in India), the treatment generates substantially more donors and donations than when the identified victim is from an out-group (Christian minority). An in-group victim increases donation rates by almost 50%, and nearly doubles funds raised. Even an identified out-group victim does better relative to unidentified group of victims.
4. We find support for reference dependent sympathy. When victims are described as currently destitute, but previously well-off, they are likely to generate 50% more donors and 33% more

average donations than someone who is destitute, but the past was left un-described. This supports the hypotheses that the chronic poor are less likely to elicit sympathy than someone who suffered a change—i.e., fell into poverty in old age.

5. We find no support of the "pennies a day" hypothesis. The monthly temporal framing generated 71% more donors and 66% more donations than the daily framing, even when the daily frame was in terms of an amount that is smaller than the price of a coffee in urban India.
6. The ratio graphs of the amount donated across conditions for the corresponding rank of the give (panel C) in Figures 1-4 show that the strength of each effect tested is extremely powerful—to the best of our knowledge, such a result has never been presented in the behavioral literature. This representation based on a paired test is more convincing that a mere means and proportion test that is typically presented in the behavioral literature.

Empirical research using field data on advertising has focused primarily on how advertising spend and timing affect market outcomes; there has been little systematic research on how advertising content affects outcomes. Our results show that varying advertising content through theoretical results identified in psychology has economically significant impact on the market outcomes in real world settings. This is particularly important as these treatments add little incremental cost, yet have dramatic impact on market outcomes.

There are of course a few caveats that we should highlight. First as with all experimental research, the effect sizes are likely a function of the particular treatments. For example, the loss treatment can be made stronger by making the losses of the victim more vivid; or we could make the ingroup effect stronger by priming religion more explicitly, and/or emphasizing geography (state or city) or linguistic connections. Similarly the effect sizes can vary across contexts. For example, our donation request is in the context of a chronic poverty condition, but if the ask is around a disastrous event (e.g., earthquake, tsunami etc.) to help destitute seniors, the effect sizes will be likely larger. Further, the cold list donation was done during tax time and the Holi holidays. The overall giving may be more muted during other seasons. As we show in the paper, the effect sizes are different for cold lists versus warm lists--—a managerially important distinction. The differences in framing effect sizes by treatment and context is similar to variations in price and advertising elasticities documented in empirical work across categories and in different shopping and media contexts, that typically gets summarized through meta-analysis over time (e.g., Tellis 1988; Kaul and Wittink 1995). Finally, one issue in managerial use of these results is whether the effects of sympathy biases might wane over time with repeated use on in competitive settings, if all fundraisers apply such ideas. As with much psychological research on framing effects such as loss aversion, endowment effects etc., we believe these effects are unlikely to fade due to repeated use or use by competitors, but these issues are worthy of testing in future work.

We hope our research continues to bridge the gap between behavioral and quantitative marketing research not just in the area of advertising, but also more broadly by triggering research agendas around field validation and conceptual replications for various behavioral theories by quantitative empirical scholars. While behavioral research focuses on identifying new theories and exploring the theoretical mechanisms underlying the psychological effects, empirical research by quantitative marketers and economists is more focused on measuring the magnitude of effects and relative effect size of alternative marketing levers in naturally occurring data. In practice, naturally occurring empirical data do not have the variations to measure psychological effects and therefore there is often the question of whether behavioral effects identified in the lab can be observed in real world settings and how economically meaningful the effect sizes are. This study demonstrates that experimental treatments based on well documented theories in psychology can be implemented in the form of experimental treatments in practical and natural field settings with a very light touch and still produce large economically relevant effects. Such research focused on measuring relative effect sizes of previously identified behavioral effects in natural settings should be valuable for not only quantitative marketers and economists interested in whether psychological theories matter in the field, but also for managers interested in choosing among the recommendations from behavioral theories as marketing levers.

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# Appendix

*Proposition: The difference in giving rates for ingroup and outgroup victims when the potential donor list consists only of ingroup members will be greater than or equal to the difference in giving rates for ingroup and outgroup victims when the donor list has a mix of ingroup and outgroup members with ingroup members being a majority in the mailing list.*

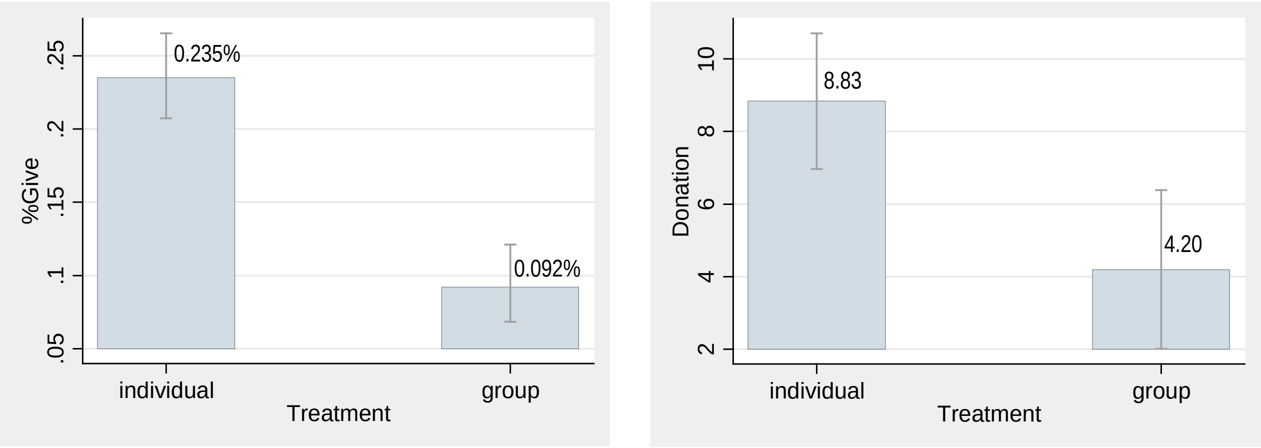
Let $\alpha$ and $(1-\alpha)$ be the proportion of ingroup and outgroup potential donors respectively in the mailing list. Let the giving rate towards ingroup and outgroup victims be $x$ and $\beta x$ respectively, where $\beta \leq 1$ by the logic that the outgroup donation rate would be at most as large as the ingroup donation rate. The table below clarifies the giving rates for ingroup and outgroup victims among potential donors from the ingroup and outgroup.

| Size | Potential Donor Base | Giving rate to Ingroup Victims | Giving rate to Outgroup Victims |
|---|---|---|---|
| $\alpha$ | Ingroup | $x$ | $\beta x$ |
| $(1-\alpha)$ | Outgroup | $\beta x$ | $x$ |

If the donor sample only had the ingroup (i.e., $\alpha = 1$ ), then the difference in the giving rate between the ingroup and outgroup victims would be $x - \beta x = (1-\beta)x$ .

When the donor list has a mix of ingroup and outgroup members whose group membership cannot be identified, the estimated giving rate for ingroup victims will be: $\alpha x + (1-\alpha)\beta x$. The estimated giving rate for the outgroup victims will be: $\alpha\beta x + (1-\alpha)x$. The difference in estimated giving rate between the ingroup and outgroup victims will be $\alpha x + (1-\alpha)\beta x - (\alpha\beta x + (1-\alpha)x) = (1-\beta)x(2\alpha - 1)$. When the ingroup members are in the majority, i.e., $\alpha \geq 0.5$, $0 \leq (2\alpha - 1) \leq 1$. Q.E.D.

**Figure 1: Identified Victim: Individual versus Group Effect**



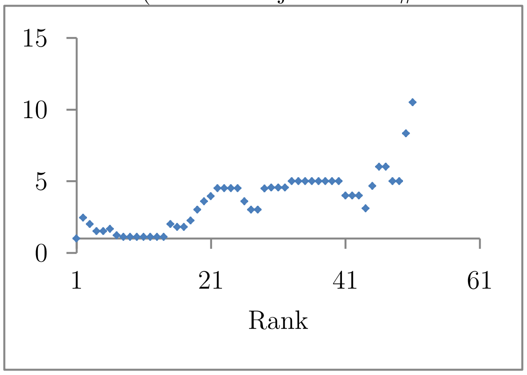
A. Donation Rate

B. Donation(₹)/mail

Ratio (individual/group)=2.55
Individual CI: (.210%, 0.264% )
Group CI: (.067%, 0.117%

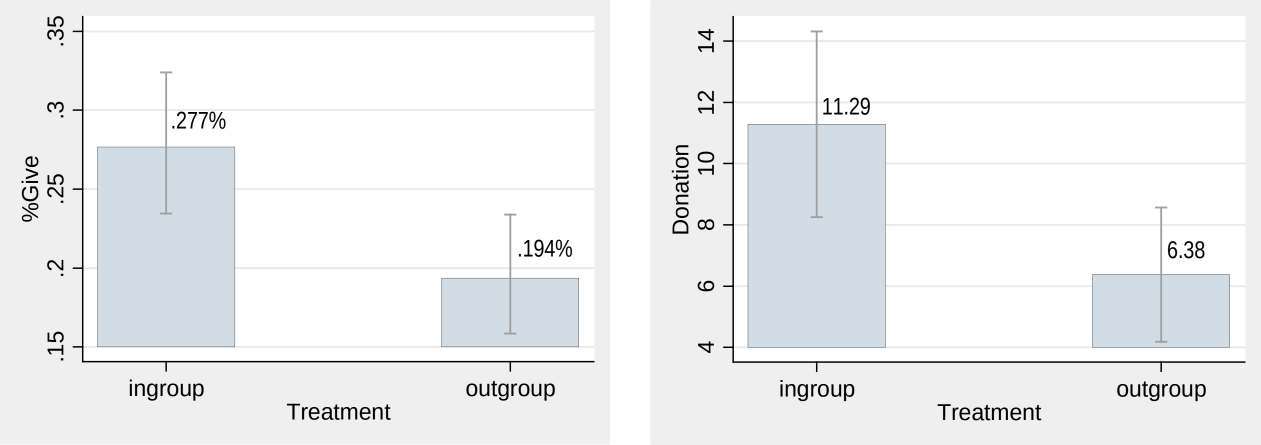
Ratio (individual/group)=2.10
Individual CI: (6.96, 10.71 )
Group CI: (2.01, 6.38)

C. Ratio of Individual/Group Donation Amounts (for rank adjusted for # of mailers)



Average Ratio (95% CI): 3.60 (3.05,4.16)

## Figure 2: In-group versus Out Group Effect



A. Donation Rate

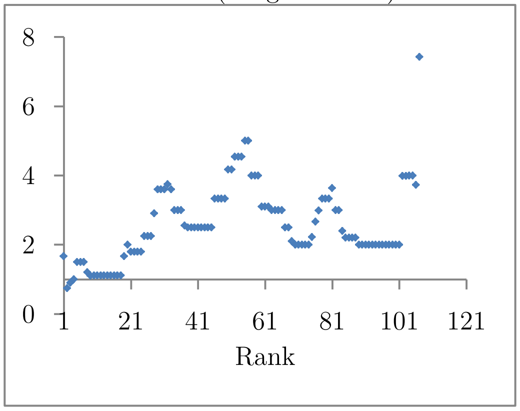
Ratio (ingroup/outgroup)=1.42
Ingroup 95% CI: (0.233%, 0.320%)
Outgroup 95% CI: (0.157%, 0.230%)

B. Donation(₹)/mail

Ratio (ingroup/outgroup)=2.55
Ingroup 95% CI: (8.25, 14.32)
Outgroup 95% CI: (4.19, 8.56)

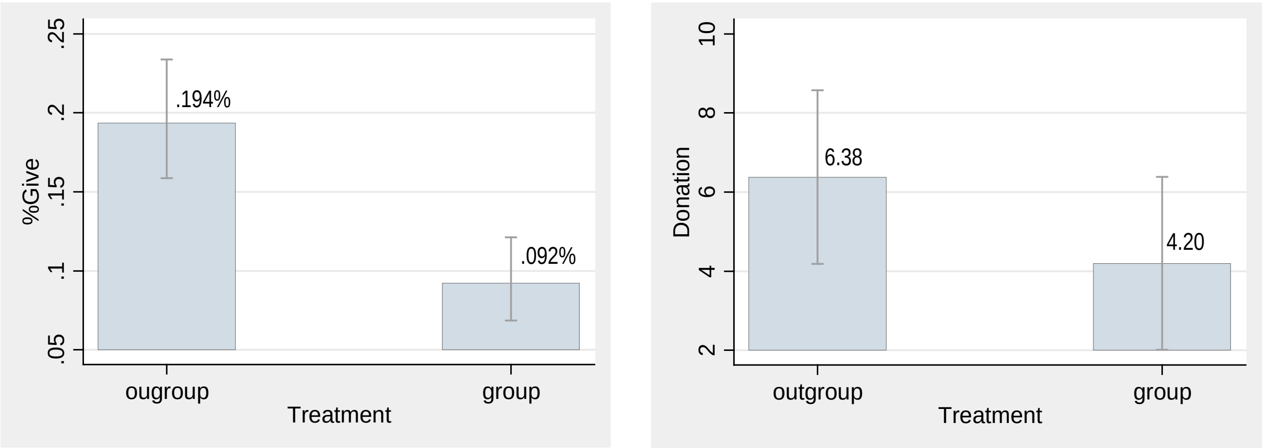
.

C. Ratio of Ingroup/Outgroup Donation
(for given rank)



Average Ratio (95% CI): 2.61 (2.40,2.82)

**Figure 3: Out-group versus Group Effect**



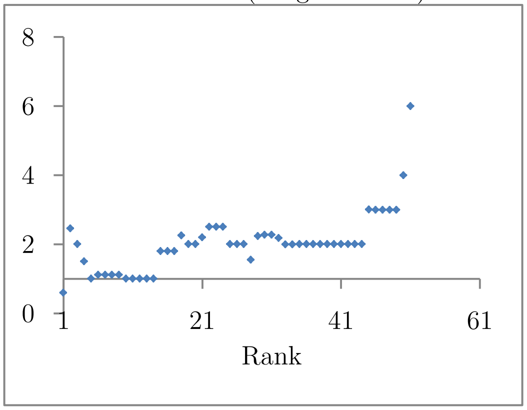
A. Donation Rate

Ratio (outgroup/group)=2.11
Outgroup 95% CI: (0.157%, 0.230%)
Group 95% CI: (0.067%, 0.117%)

B. Donation(₹)/mail

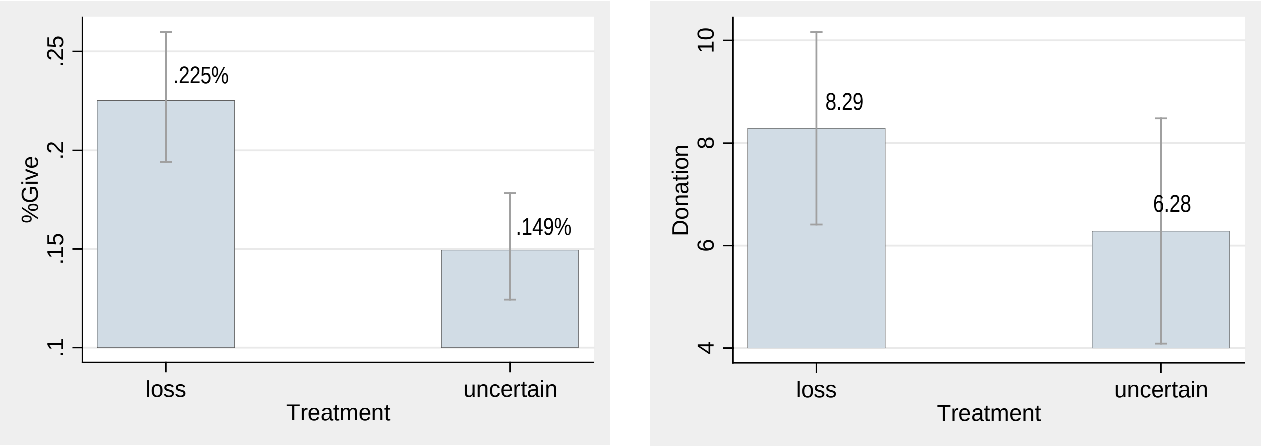
Ratio (individual/group)=1.52
Outgroup 95% CI: (4.19, 8.56)
Group 95% CI: (2.01, 6.38)

C. Ratio of Out-group/Group Donation
(for given rank)



Average Ratio (95% CI): 2.04 (1.80, 2.28)

Figure 4: Reference Dependence: Loss Versus Uncertain Reference Effect



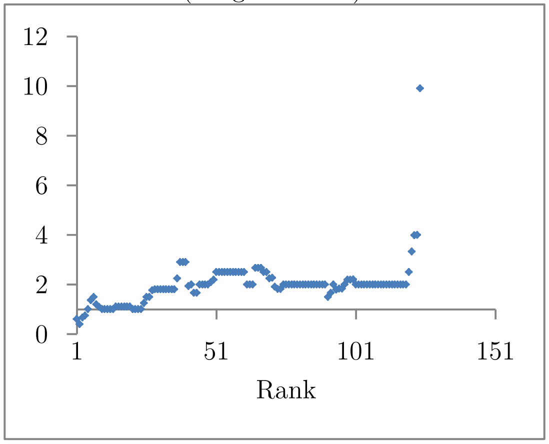
A. Donations Per Mailing

Ratio (loss/uncertain)=1.51
Loss 95% CI: (0.193%, 0.257%)
Uncertain 95% CI: (0.123%, 0.176%)

B. Donation(₹)/mail

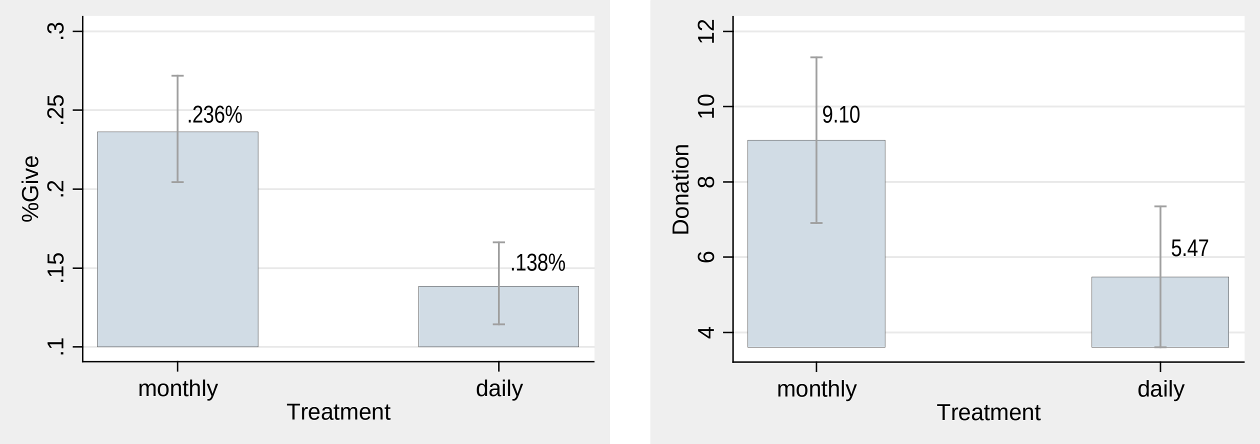
Ratio (loss/uncertain)=1.32
Loss CI: (6.41, 10.17)
Uncertain CI: (4.09, 8.48)

C. Ratio of Loss/Uncertain Donation
(for given rank)



Average Ratio (95% CI): 1.97 (1.81, 2.14)

**Figure 5: Temporal Framing: Monthly versus Daily Ask**



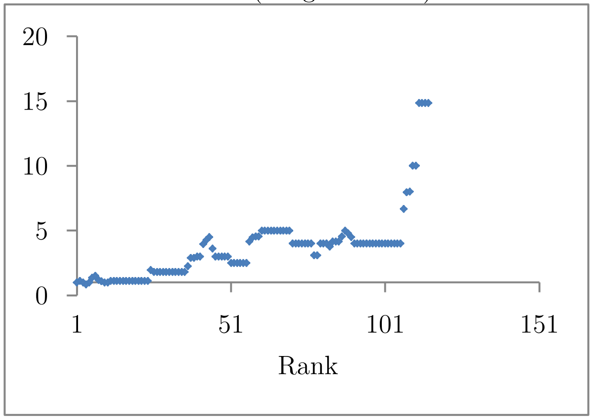
A. Donations Per Mailing

Ratio (monthly/daily)=1.71
Monthly CI: (0.203%, 0.269%)
Daily CI: (0.113%, 0.163%)

B. Donation(₹)/mail

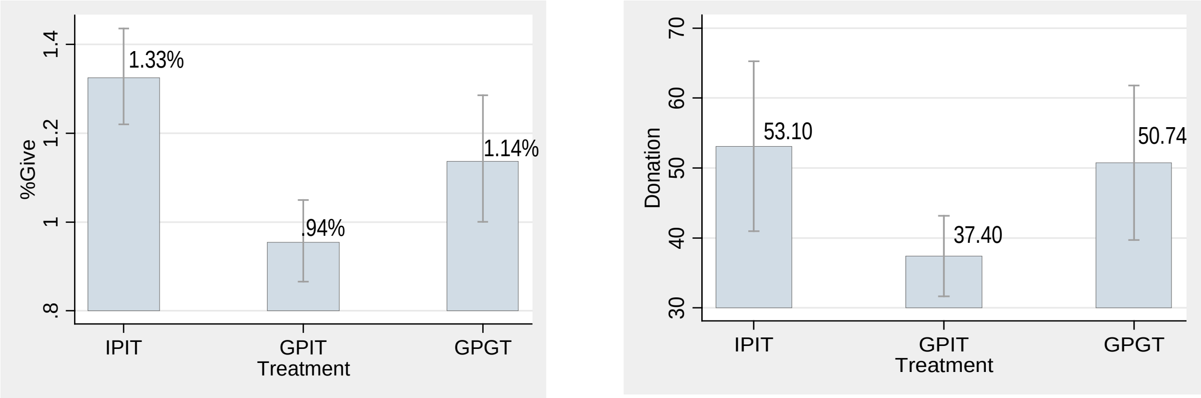
Ratio (monthly/daily)=1.66
Monthly CI: (6.90, 11.0)
Daily CI: (3.60, 7.34)

C. Ratio of Monthly/Daily Donation
(for given rank)



Average Ratio (95% CI): 3.69 (3.17, 4.20)

## Figure 6: Past Donor Experiment



A. Donation Rate

B. Donation(₹)/mail

IPIT 95% CI: (1.22%, 1.43%)
GPIT 95% CI: (0.87%, 1.05%)
GPGT 95% CI: (1.00%, 1.28%)

IPIT 95% CI: (40.97, 65.23)
GPIT 95% CI: (31.66, 43.15)
GPGT 95% CI: (39.72, 61.77)

## Table 1: New Donor Experiment: Experimental Treatments

| Treat-ment | Mnemonic | Individual/ Group | In-group / Out-group | Reference Loss/Uncertain | Monthly/ Daily |
|---|---|---|---|---|---|
| 1 | IHLM | Individual | Hindu | Loss | Monthly |
| 2 | IHUM | Individual | Hindu | Uncertain | Monthly |
| 3 | IHLD | Individual | Hindu | Loss | Daily |
| 4 | IHUD | Individual | Hindu | Uncertain | Daily |
| 5 | ICLM | Individual | Christian | Loss | Monthly |
| 6 | ICUM | Individual | Christian | Uncertain | Monthly |
| 7 | ICLD | Individual | Christian | Loss | Daily |
| 8 | ICUD | Individual | Christian | Uncertain | Daily |
| 9 | G_LM | Group | NA | Loss | Monthly |
| 10 | G_UM | Group | NA | Uncertain | Monthly |
| 11 | G_LD | Group | NA | Loss | Daily |
| 12 | G_UD | Group | NA | Uncertain | Daily |
| 13 | Control | NA | NA | NA | NA |

**Table 2a: New Donor Experiment: Summary of Experiment Outcomes**

| Treatment | Mnemonic | # Mailed | %Donate | ₹/Mailing | ₹/Donor |
|---|---|---|---|---|---|
| 1 | IHLM | 13826 | 0.36% | 16.28 | 4501 |
| 2 | IHUM | 13832 | 0.27% | 9.29 | 3474 |
| 3 | IHLD | 13823 | 0.34% | 11.96 | 3516 |
| 4 | IHUD | 13669 | 0.14% | 7.63 | 5561 |
| 5 | ICLM | 13832 | 0.34% | 12.24 | 3603 |
| 6 | ICUM | 13805 | 0.22% | 6.45 | 2967 |
| 7 | ICLD | 13820 | 0.14% | 2.93 | 2134 |
| 8 | ICUD | 13690 | 0.08% | 3.88 | 4886 |
| 9 | G_LM | 13859 | 0.11% | 3.77 | 3480 |
| 10 | G_UM | 13682 | 0.12% | 6.59 | 5341 |
| 11 | G_LD | 13876 | 0.06% | 2.59 | 3996 |
| 12 | G_UD | 13682 | 0.07% | 3.85 | 5339 |
| 13 | Control | 15506 | 0.11% | 4.30 | 3958 |
| | **Overall** | **184396** | **0.17%** | **6.98** | **3993** |
| | **Average for 12 Treatments** | **165982** | **0.19%** | **7.29** | **3889** |

**Table 2b: New Donor Experiment: Logistic Regression on Donation Choice**

| | Logistic Regression on Donation Choice | | | Tobit Regression on Donation Amounts | |
|---|---|---|---|---|---|
| | Coefficient (std. err) | Odds Ratio | Z | Coefficient (std. err) | t-stat |
| Individual | 0.743*** | 2.10 | 4.37 | 3095*** | 4.08 |
| | (.170) | | | (759) | |
| Ingroup | 0.358*** | 1.41 | 2.84 | 1756*** | 2.97 |
| | (.126) | | | (591) | |
| Loss | 0.411*** | 1.51 | 3.55 | 1786*** | 3.34 |
| | (.116) | | | (535) | |
| Month | 0.535*** | 1.71 | 4.55 | 2438*** | 4.46 |
| | (.118) | | | (546) | |
| Intercept | -7.52*** | | -43.42 | -47312*** | -18.50 |
| | (.173) | | | (2557) | |
| N | 165982 | | | | |

Base Treatment is: Group-Uncertain-Daily Condition

***p< 0.01

### Table 3a: Survey Based Experiment: Descriptive Statistics

|  | N | Likelihood to Give (1-10) | Std. Dev | Past Give | Education | Income |
|---|---|---|---|---|---|---|
| Hindu-Sushila | 139 | 7.50 | 2.48 | 0.24 | 4.14 | 4.14 |
| Hindu-Shirley | 155 | 6.97 | 2.53 | 0.27 | 4.12 | 4.08 |
| Christian-Sushila | 57 | 5.98 | 2.99 | 0.26 | 4.35 | 5.54 |
| Christian-Shirley | 41 | 6.98 | 2.74 | 0.17 | 4.20 | 4.15 |

### Table 3b: Survey Based Experiment-1: Likelihood of Giving

|  | Coefficient (std. err) | t-stat | Coefficient (std. err) | t-stat |
|---|---|---|---|---|
| Hindu Sushila | 0.527* | 1.73 | 0.503* | 1.73 |
|  | (.305) |  | (.291) |  |
| Christian Shirley | 1.002** | 1.88 | 1.063** | 2.07 |
|  | (.533) |  | (.515) |  |
| Hindu | 0.991*** | 2.720 | 1.053*** | 2.72 |
|  | (.403) |  | (.388) |  |
| Past giving |  |  | 1.566*** | 5.36 |
|  |  |  | (.292) |  |
| Diploma[21] |  |  | 1.731** | 2.04 |
|  |  |  | (.850) |  |
| Bachelor's degree |  |  | 2.047*** | 3.23 |
|  |  |  | (.634) |  |
| Graduate Degree |  |  | 2.078*** | 3.20 |
|  |  |  | (.649) |  |
| intercept | 5.979*** | 17.31 | 2.807*** | 3.94 |
|  | (.345) |  | (.712) |  |
| N | 392 |  | 392 |  |

Base Treatment is: Christian-Sushila

Base level of Education is less than 12th Grade

*p<0.1; **p<0.05, ***p<0.01

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[21] A Diploma is 3 year vocational degree from a technical training institution that is entered after 10th grade. It is lower in prestige than a three or four year Bachelor's degree that is entered after 12th grade.

**Table 3c: Survey Based Experiment-2: HelpAge Evaluations**

| | Good Cause | Well-Managed | Positive Image |
|---|---|---|---|
| | Coeff<br>(t-stat) | Coeff<br>(t-stat) | Coeff<br>(t-stat) |
| Sushila | 0..093<br>(.46) | 0.035<br>(.17) | 0.062<br>(.31) |
| Past giving | 0.691***<br>(3.13) | 0.683***<br>(2.99) | 0.364<br>(1.64) |
| Intercept | 7.792***<br>(35.82) | 7.531***<br>(33.53) | 7.966***<br>(36.28) |
| N | 252 | 252 | 252 |

Education is not statistically significant, but increases standard errors, so they are not included.
The coefficients on Sushila remain qualitatively similar without Past giving as covariate.
*p<0.1; **p<0.05, ***p<0.01

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**Table 4a: Past Donor Experiment: Descriptive Statistics on Past Behavior and Experiment Outcomes**

| Treat-ment | Description (Mnemonic) | # Mail | Recency | Past Freq | ₹ Past Amt | % Donate | ₹/ Mail | ₹/ Donor |
|---|---|---|---|---|---|---|---|---|
| 1 | Individual Photo-Individual Text (IPIT) | 44000 | 0.62 | .920 | 3066 | 1.325% | 53.10 | 4007 |
| 2 | Group Photo-Individual Text (GPIT) | 43999 | 0.63 | .923 | 2939 | 0.954% | 37.40 | 3918 |
| 3 | Group Photo-Group Text (GPGT) | 22000 | 0.63 | .927 | 2980 | 1.136% | 50.74 | 4465 |
| | Overall | 109999 | 0.63 | 0.92 | 2981 | 1.14% | 45.03 | 4069 |

### Table 4b: Past Donor Experiment: Logistic Regression on Donation Choice

| | Model 1 | | | Model 2 | | |
|---|---|---|---|---|---|---|
| | Estimate | Odds | Z | Estimate | Odds | Z |
| | (Std. Err) | Ratio | | (Std. Err) | Ratio | |
| Individual Photo Individual Text | 0.16* | 1.16 | 2.04 | 0.15* | 1.16 | 1.99 |
| (IPIT) | (0.084) | | | (.08) | | |
| Group Photo- Individual Text | -0.18** | 0.83 | -2.19 | -0.018** | 0.83 | -2.22 |
| (GPIT) | (0.079) | | | (0.075) | | |
| Donation in Past Year? | | | | 0.61*** | 1.84 | 4.99 |
| (Recency) | | | | (0.123) | | |
| # Donations in 5 years | | | | 0.74*** | 2.09 | 38.41 |
| (Frequency) | | | | (0.02) | | |
| Total Donations in 5 Years | | | | -4.11e-3* | 0.99 | -1.85 |
| (Monetary Value in thousands) | | | | (2.51e-6) | | |
| Intercept | -4.46*** | 0.011 | -70.21 | -6.15 | 0.002 | -50.46 |
| | (0.063) | | | (0.121) | | |
| N | 109999 | | | 109999 | | |

Base Treatment is: Group Photo-Group Text (GPGT) Condition

*p<0.1; **p<0.05, ***p<0.01

### Table 4c: Past Donor Experiment: Tobit Regression on Donation Amount

| | Model 1 | | Model 2 | |
|---|---|---|---|---|
| | Estimate | t-stat | Estimate | t-stat |
| | (Std. Err) | | (Std. Err) | |
| Individual Photo Individual | 799* | 1.85 | 739* | 1.68 |
| Text (IPIT) | (431) | | (440) | |
| Group Photo- Individual Text | -1042** | -2.32 | -1094** | -2.36 |
| (GPIT) | (450) | | (459) | |
| Donation in Past Year? | | | 1354*** | 2.39 |
| (Recency) | | | (567) | |
| # Donations in 5 years | | | 4274*** | 27.86 |
| (Frequency) | | | (153) | |
| Total Donations in 5 Years | | | 0.02*** | 3.29 |
| (Monetary Value) | | | (0.006) | |
| Intercept | -34178*** | -37.49 | -39429*** | -35.63 |
| | (914) | | (1106) | |
| Sigma | -34178*** | | 13850*** | |
| | (914) | | (328) | |
| N | 109999 | | 109999 | |
| N (Left Censored at 0) | 108746 | | 108746 | |
| N (Uncensored) | 1253 | | 1253 | |

Base Treatment is: Group Photo-Group Text (GPGT) Condition

*p<0.1; **p<0.05, ***p<0.01