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

By

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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 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. This can 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.

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., Croson and Shang 2008, Shang and Croson 2009) and social pressure (DellaVigna, Malmendier and List 2012) on donor behavior. While there is a large volume of behavioral research in the laboratory on the persuasive effects of advertising content, there is little field based empirical research in general on the persuasive 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 effects of various types of persuasive advertising appeals identified by the psychology literature on donation behavior through large scale field experiments.

Academic research by empirical scholars on the persuasive effects of advertising using field data typically focus on estimating the relationship between the volume of the advertising, frequency and timing on market outcomes such as sales and market shares;\(^1\) there is virtually no field research on quantifying how different elements of advertising content affects market outcomes.\(^2\) This 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.

In general, psychologists have found that emotions work better to motivate people to action than cognition; hence treatments that generate an emotional response are more likely to be

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\(^1\) See DellaVigna and Gentzkow (2010) for a review of the empirical evidence on persuasive advertising.

\(^2\) Bertrand et al. (2010) is a notable exception. 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).
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). In particular, sympathy can be increased by reducing the perceived social distance from the victim (Small 2010). For example, social distance can be reduced if the victim is from the same in-group as the target donor (in-group effect). Similarly, perceived social distance can be reduced by identifying an individual victim to a potential donor (the identified victim effect). Also, 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 2009; reference dependent sympathy effect). We use these insights to generate three advertising treatments in the experiment. They are: (1) the identified victim effect (2) the in-group effect, (3) reference dependent sympathy effect. These effects are called “sympathy biases” because sympathy is not generated in proportion to the actual needs of the victims, but by how the victim’s misfortune is framed. From a charity’s perspective, knowledge of such sympathy biases can inform sympathy appeals in order to persuade potential donors to give more. Specifically, using appeals framed to reduce perceived social distance with respect to the victims, a charity can generate greater sympathy for victims and generate more giving.

Charities often temporally reframe the amount of an aggregate donation or spend into a series of smaller ongoing expenses even though the aggregate donation or spend itself remains aggregated. A $365 annual insurance premium or donation to NPR seems more affordable when framed as $1 a day. 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 one large amount, because multiple losses create greater disutility than one large loss. 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 they sends out mailers to a cold list (purchased from a third party) 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 are relatively large in magnitude relative to incomes in India. 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 is targeted a warm list of 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 conducted a few treatments to test our conjecture whether the effect vanishes for past donors. As expected, the percentage impact on donations for our previously largest effect falls is lower; 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 relative impact in new donor acquisition, the economic impact in generating donations is very significant among both new and existing donors.
Methodologically, this paper is part of a small but growing empirical literature using field experiments to measure advertising effects. In a landmark set of field experiments, Eastlack and Rao (1989) reports 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. In recent years, the field experiment tradition for measuring advertising effects has gained increased interest. Using online field experiments, Sahni (2012) tests for alternative mechanisms by which the temporal spacing of advertising impacts sales; while Schwartz (2012) tests for the effect of ad sizes and position in banner advertisements to drive click-through.

More broadly, we believe 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 phenomena in controlled laboratory settings; typically testing each effect in isolation. As the focus is on isolating and understanding the mechanism underlying novel psychological effects, there is relatively little emphasis on whether these effects replicate in field settings, whether the magnitude of the effects are economically important; and what the relative magnitudes of the different effects are on the outcome of interest. In contrast, quantitative scholars focused on empirical work, are typically interested in measuring the relative effects of different marketing actions on an outcome of interest using field data and their potential economic impact; managers use these insights to choose the most effective marketing actions. This paper complements and builds on behavioral work by illustrating how we can leverage insights from alternative behavioral theories to drive managerial action. By simultaneously experimenting on multiple types of content effects motivated by the psychology literature in driving donations on the field, we are able to create the necessary variation in field data to test whether the effects replicate in the field, understand the relative magnitude of the effects due to alternative theories. We are also able to measure the economic relevance of these subtle psychological effects for
managerial action. We emphasize that our goal is to be complementary to behavioral research in that we do not seek to generate or test novel theories, which are most efficiently isolated in controlled laboratory settings, but to assess their managerial and economic relevance in the field.

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.\(^3\) 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.\(^4\) 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

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\(^3\) 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.aaa.org/news/agency/Pages/120511_groupm_forecast.aspx].

\(^4\) The industry had traditionally bundled its creative and media services and hence share of spend on creative is not available. (See Horsky et al 2011; Silk and Berndt 2003)
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.

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.\(^5\) 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.\(^6\) A notable exception is Bertrand et al. (2010), who test the effectiveness of a number of non-informative advertising cues and prices in a direct mailer campaign to study their impact on loan uptake from a credit card lender using a randomized field experiment.

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 (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.

\(^5\) Levitt and List (2007) provide many reasons for why the laboratory findings need to be validated on the field.
\(^6\) 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.
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), 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, Singh, and Bendapudi 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. Croson and Shang (2008) and 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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7 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, Shiv, and Bettman 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

As discussed in the introduction, our five hypotheses are based on the literature on sympathy biases and framing. The first three hypotheses are related to how social distance impacts sympathy; the fourth addresses the reference dependence sympathy bias effect. Finally, the fifth hypothesis is related to temporal reframing, i.e., monthly versus daily framing of the ask. We discuss each of these 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; Epstein, 1994; Kahneman and Frederick, 2002; Sloman, 1996), Small and Loewenstein (2005) argue that identifiable victims reduce social distance and thereby generate more sympathy because they invoke the affective (emotional) system (e.g., Small and Loewenstein 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 (Epstein, 1994; 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., Baron, 1997; Featherstonhaugh, et al. 1997; 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 1991 and 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, 2005; 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; Tversky and Kahneman, 1991). 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 aggregate donation or spend into a series of smaller ongoing expense even though the aggregate donation or spend itself remains aggregated. Such strategies are used in a variety of contexts, ranging from insurance, magazine subscriptions, durable goods and charitable donations. A $365 annual insurance premium or donation to NPR seems more affordable when framed as $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 $365 transaction be perceived more favorably if temporally reframed as $30 per month or $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 apriori 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.\textsuperscript{8} 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.\textsuperscript{9} 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 or 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.

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,\textsuperscript{10} the low response rates of about 0.1\%, implies that actual money raised per mailing is only around ₹3.

\textsuperscript{8} The laws are similar in spirit to laws in developed world designed to prevent neglect of children.

\textsuperscript{9} HelpAge India Brochure accessed March 1, 2012 from website \url{http://www.helpageindia.org/pdf/Organizational_Brochure.pdf}

\textsuperscript{10} The exchange rate in May 2011 averaged ₹44.93 (Indian Rupees) for $1 (U.S. Dollar). (www.xrate.com)
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 operationalize the test of the identified victim effect using two different types of treatments: an individual (I) and group (G) condition. Below we present an example of the individual and group condition. 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).

**Individual Condition**

<table>
<thead>
<tr>
<th>Photo of Sushila</th>
<th>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.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>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.</td>
</tr>
<tr>
<td></td>
<td>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.</td>
</tr>
</tbody>
</table>

**Group Condition**

<table>
<thead>
<tr>
<th>Photo Collage of four unnamed ladies</th>
<th>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.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>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.</td>
</tr>
<tr>
<td></td>
<td>Your tax deductible donation of ₹9000 a year (that is just ₹750 a month) helps these</td>
</tr>
</tbody>
</table>
and other people like them 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 a group of four women (who are shown in a picture collage) and describe the group.

We implement the in-group and out-group treatment as follows: 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).11

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

---

11 Christians constitute only 2.5% of India’s population and are a reasonable out-group for our purposes. For robustness, we tested our results by omitting data from states with relatively large Christian populations such as Kerala (19%) and Goa (27%). Note that Kerala and Goa are relatively small states in terms of populations, relative to other states in which HelpAge targeted for new donor acquisition.
same amount is framed as ₹750 a month for the monthly condition and ₹25 a day for the daily condition.\(^\text{12}\)

**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 \(2 \times 2 \times 2 = 8\) conditions in the individual treatments. Within the group treatment, we do not have the in-group and out-group condition. So we only have the remaining \(2 \times 2 = 4\) 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.\(^\text{13}\)

*** Insert Table 2 here ***

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

\(^{12}\) 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.

\(^{13}\) 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.
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 intrinsically 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.\(^{14}\) 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.

\(^{14}\) 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.
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. Thus the relative risk for the individual treatment is 2.55 times the rate of donations in the group treatments. This relative risk is significantly different from 1 as indicated by the confidence interval (1.89, 3.44).

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 ₹4.29 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, suggesting that it does evoke more sympathy among potential donors. 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.

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 43% with an in-group individual (Relative risk is 1.43), 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 mailers were 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.

C. Out-group “Identified Victim” versus “Unidentified” Group

Figure 3 compares the out-group “identified victim” effect against the “unidentified” group. From pane; 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 (Relative risk is 2.10), suggesting that the identified victim effect is stronger than the in-group effect in inducing sympathy and giving. The effect is clearly statistically significant, given the 95% confidence interval of (1.50, 2.93).

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 ₹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, suggesting that the identified out-group generates more sympathy than the group condition. 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%. Overall, the number of donors can be increased by 51% with an in-group individual (Relative risk is 1.51). The difference is statistically significant as reflected in the 95% confidence interval for relative risk (1.20, 1.88).

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. However, this is not much of a concern in our experiment, given that the socioeconomic status of the potential donors is much higher than those of school teachers, because the potential donor list consists of a small group of high net worth individuals (around 185,000 individuals, a small fraction of the overall Indian population) in India. Given that school teachers are an unlikely in-group for these potential donors, and possibly an out-group in terms of socioeconomic status, our effect sizes are likely to be
attenuated and may be a lower bound. Nevertheless, it would be useful to explore this issue in future 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% (relative risk 1.71). The effect is statistically significant, with a confidence interval of (1.36, 2.15).

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 donation 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), 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. We find that both the in-group and out-group conditions increase the number of donors relative to the group condition. The increase is statistically significant. The in-group condition increases the odds
of donations three times relative to the group condition. Even the out-group condition increases the odds of donation twice relative to the group effect. Thus the identified victim effect is substantial; even an identified out-group victim overwhelms 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%. It should be noted that the odds ratios reported by regression effects are virtually identical to the relative risks reported earlier when we tested pairs at a time, because of (1) the factorial design and (2) roughly equal number of mailings to each of the treatments.

The tobit regression results show that our treatments significantly affect the donation amounts. Specifically, we find that the in-group identified victim treatment 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 ₹1787 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 strong statistical and economic significance of advertising content effects.

6 Robustness Check: Raising Donations from Past Donors

Thus far, we have demonstrated that advertising content has very large effects on both donation rates and amounts raised. The odds of giving increasing 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. Given these large effects, a natural question that arises is: Did we stumble on to particularly favorable conditions in the real world where these effects are uncharacteristically strong? Are there conditions when these effects may not exist or be far more muted?

We conjectured that sympathy biases may have relatively strong relative 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 and perhaps insignificant 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.

**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 ascendency 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.

<table>
<thead>
<tr>
<th>Group Photo-Individual Text Condition</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Photo Collage</strong></td>
</tr>
<tr>
<td>of four</td>
</tr>
<tr>
<td>unnamed ladies</td>
</tr>
<tr>
<td><strong>These ladies share a common story. For example, Sushila worked as a school teacher and retired comfortably.</strong> But then she became destitute when her husband passed away and other family members refused to support her.</td>
</tr>
<tr>
<td><strong>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. 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.</strong></td>
</tr>
</tbody>
</table>

24
Experimental Design

The three treatments (as described above) and the number of mailings for the three treatments and descriptive statistics are listed in Table 4. 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 2 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. Nevertheless the relative risk is still greater with the individual condition at 1.17, with the 95% confidence interval being (1.01, 1.34). ₹/mail is also higher at ₹53.10 for the individual condition, relative to ₹50.7 for the group condition, an increase of 4.7%. 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 much more muted. Given that the number of donors and the amount of money raised with the warm list is about 10 times greater, the 17% 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.

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. In hindsight, it appears that the individual text as an example where otherwise the photo and initial introduction are about the group, does not moderate the identified victim effect, but instead destroys the fluency of the message, by mixing up a group story with an individual example.

As before, we also report the results of the logistic and tobit regressions for donation choice and donation amounts. Indeed the results reported under model 1 in Tables 5a and 5b are both qualitatively and quantitatively identical to the paired treatment comparison results discussed in the previous paragraph. Further, when using the warm list, we have information on past donations. So in Model 2, we report the results of the logistic and tobit regressions, controlling for donor heterogeneity exhibited through past donation choices. We use the standard controls used in the direct marketing literature 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). 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. Higher monetary value of past donations has no significant impact on the likelihood of giving, but does predict greater current dollar value of donations.
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. Even among past donors, donation rates and ₹/mail improve by about 15% when we use an in-group identified victim treatment relative to the group treatment.

2. We find significant evidence of the identified victim effect; an individually identified victim is likely to generate over two and a half times (relative risk 2.55) 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%, (relative risk 1.44) and nearly doubles funds raised. However 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 (relative risk of 1.51) 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 persuasion effects 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. Second, like all experimental research and empirical work using field data, the effect sizes of the different sympathy biases are a function of the empirical context. While we believe the relative magnitudes are likely preserved across contexts, additional empirical work with different treatments and contexts are necessary. In this paper, we showed how the effect sizes vary in in different empirical
contexts by measuring the effects on cold versus warm lists—a managerially important distinction. This is similar to variations in price and advertising elasticities documented in empirical work, 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.

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 replication across varied experimental treatments and contexts 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 very subtle theories in psychology implemented in the form of experimental treatments can be implemented with a light touch in practical and natural field settings 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 economists interested in whether psychological theories matter in the field, but also for managers interested in applying such behavioral theories in practice as marketing levers.
References


Small, Deborah A. (2010), 'Reference-dependent sympathy,' Organizational behavior and human decision processes, 112(2), 151-60.


Figure 1: Identified Victim: Individual versus Group Effect

A. Donation Rate

<table>
<thead>
<tr>
<th></th>
<th>Individual</th>
<th>Group</th>
</tr>
</thead>
<tbody>
<tr>
<td>Donation Rate</td>
<td>0.24%</td>
<td>0.09%</td>
</tr>
</tbody>
</table>

Relative Risk (95% CI): 2.55 (1.89, 3.44)

B. Donation(₹)/mail

<table>
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<tr>
<th></th>
<th>Individual</th>
<th>Group</th>
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<tbody>
<tr>
<td>Donation(₹)</td>
<td>₹8.83</td>
<td>₹4.20</td>
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</table>

Ratio: 2.10

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

<table>
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<tr>
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<th>In-Group</th>
<th>Out-Group</th>
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<tbody>
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<td>Donation Rate</td>
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<td>0.19%</td>
</tr>
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</table>

Relative Risk (95% CI): 1.43 (1.12, 1.83)

B. Donation (₹)/mail

<table>
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<tr>
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<th>Out-Group</th>
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<td>Donation (₹)</td>
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<td>₹ 6.38</td>
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Ratio: 1.77

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

Out-Group: 0.19%
Group: 0.09%

Relative Risk (95% CI): 2.10 (1.50, 2.93)

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

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

B. Donation(₹)/mail

Out-Group: ₹ 6.38
Group: ₹ 4.20

Ratio: 1.52
Figure 4: Reference Dependence: Loss Versus Uncertain Reference Effect

A. Donations Per Mailing

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</tr>
<tr>
<td>0.15%</td>
<td>0.15%</td>
<td></td>
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<tr>
<td>0.10%</td>
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<td>0.05%</td>
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<td>0.00%</td>
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</table>

Relative Risk (95% CI): 1.51 (1.20, 1.88)

B. Donation(₹)/mail

<table>
<thead>
<tr>
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</thead>
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</tr>
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</tr>
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<td></td>
</tr>
<tr>
<td>0.00</td>
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</table>

Ratio: 1.33

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

Relative Risk (95% CI): 1.97 (1.81, 2.14)
Figure 5: Temporal Framing: Monthly versus Daily Ask

A. Donations Per Mailing

![Donations Per Mailing Graph]

Relative Risk (95% CI): 1.71 (1.36, 2.15)

B. Donation(₹)/mail

![Donation(₹)/mail Graph]

Ratio: 1.66

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

![Ratio of Monthly/Daily Donation Graph]

Relative Risk (95% CI): 3.69 (3.17, 4.20)
Figure 6: Past Donor Experiment

A. Donation Rate

B. Donation(₹)/mail
Table 1: New Donor Experiment: Experimental Treatments

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Mnemonic</th>
<th>Individual/Group</th>
<th>In-group / Out-group</th>
<th>Reference Loss/Uncertain</th>
<th>Monthly/Daily</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>IHLM</td>
<td>Individual</td>
<td>Hindu</td>
<td>Loss</td>
<td>Monthly</td>
</tr>
<tr>
<td>2</td>
<td>IHUM</td>
<td>Individual</td>
<td>Hindu</td>
<td>Uncertain</td>
<td>Monthly</td>
</tr>
<tr>
<td>3</td>
<td>IHLD</td>
<td>Individual</td>
<td>Hindu</td>
<td>Loss</td>
<td>Daily</td>
</tr>
<tr>
<td>4</td>
<td>IHUD</td>
<td>Individual</td>
<td>Hindu</td>
<td>Uncertain</td>
<td>Daily</td>
</tr>
<tr>
<td>5</td>
<td>ICLM</td>
<td>Individual</td>
<td>Christian</td>
<td>Loss</td>
<td>Monthly</td>
</tr>
<tr>
<td>6</td>
<td>ICUM</td>
<td>Individual</td>
<td>Christian</td>
<td>Uncertain</td>
<td>Monthly</td>
</tr>
<tr>
<td>7</td>
<td>ICLD</td>
<td>Individual</td>
<td>Christian</td>
<td>Loss</td>
<td>Daily</td>
</tr>
<tr>
<td>8</td>
<td>ICUD</td>
<td>Individual</td>
<td>Christian</td>
<td>Uncertain</td>
<td>Daily</td>
</tr>
<tr>
<td>9</td>
<td>G_LM</td>
<td>Group</td>
<td>NA</td>
<td>Loss</td>
<td>Monthly</td>
</tr>
<tr>
<td>10</td>
<td>G_UM</td>
<td>Group</td>
<td>NA</td>
<td>Uncertain</td>
<td>Monthly</td>
</tr>
<tr>
<td>11</td>
<td>G_LD</td>
<td>Group</td>
<td>NA</td>
<td>Loss</td>
<td>Daily</td>
</tr>
<tr>
<td>12</td>
<td>G_UD</td>
<td>Group</td>
<td>NA</td>
<td>Uncertain</td>
<td>Daily</td>
</tr>
<tr>
<td>13</td>
<td>Control</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
</tbody>
</table>

Table 2: New Donor Experiment: Descriptive Statistics

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

<table>
<thead>
<tr>
<th></th>
<th>Logistic Regression on Donation Choice</th>
<th>Tobit Regression on Donation Amounts</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>Odds Ratio</td>
</tr>
<tr>
<td>in-group</td>
<td>1.10***</td>
<td>3.01</td>
</tr>
<tr>
<td>out-group</td>
<td>0.74***</td>
<td>2.10</td>
</tr>
<tr>
<td>loss</td>
<td>0.41***</td>
<td>1.51</td>
</tr>
<tr>
<td>month</td>
<td>0.54***</td>
<td>1.71</td>
</tr>
<tr>
<td>intercept</td>
<td>-7.52***</td>
<td>-43.42</td>
</tr>
</tbody>
</table>

Base Treatment is: Group-Uncertain-Daily Condition

***p < 0.01

Table 4: Past Donor Experiment: Descriptive Statistics

<table>
<thead>
<tr>
<th>Treatment (Mnemonic)</th>
<th># Mailed</th>
<th>%Donate</th>
<th>₹/Mailing</th>
<th>₹/Donor</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Individual Photo-Individual Text (IPIT)</td>
<td>44000</td>
<td>1.325%</td>
<td>53.10</td>
<td>4007</td>
</tr>
<tr>
<td>2 Group Photo-Individual Text (GPIT)</td>
<td>43999</td>
<td>0.954%</td>
<td>37.40</td>
<td>3918</td>
</tr>
<tr>
<td>3 Group Photo-Group Text (GPGT)</td>
<td>22000</td>
<td>1.136%</td>
<td>50.74</td>
<td>4465</td>
</tr>
<tr>
<td>Overall</td>
<td>109999</td>
<td>1.14%</td>
<td>45.03</td>
<td>4069</td>
</tr>
</tbody>
</table>
Table 5a: Past Donor Experiment: Logistic Regression on Donation Choice

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate (Std. Err)</td>
<td>Odds Ratio</td>
</tr>
<tr>
<td>Individual Photo Individual Text</td>
<td>0.16* (0.084)</td>
<td>1.16 (.08)</td>
</tr>
<tr>
<td>Group Photo Individual Text</td>
<td>-0.18** (0.079)</td>
<td>0.83 (0.123)</td>
</tr>
<tr>
<td>Donation in Past Year? (Recency)</td>
<td>0.61*** (0.123)</td>
<td>1.84 (0.02)</td>
</tr>
<tr>
<td># Donations in 5 years (Frequency)</td>
<td>0.74*** (0.02)</td>
<td>2.09 (0.02)</td>
</tr>
<tr>
<td>Total Donations in 5 Years (Monetary Value)</td>
<td>-4.11e-6* (2.51e-6)</td>
<td>0.99</td>
</tr>
<tr>
<td>Intercept</td>
<td>-4.46*** (0.036)</td>
<td>-123.41</td>
</tr>
</tbody>
</table>

Base Treatment is: Group Photo-Group Text Condition

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

Table 5b: Past Donor Experiment: Tobit Regression on Donation Amount

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate (Std. Err)</td>
<td>Estimate (Std. Err)</td>
</tr>
<tr>
<td>Individual Photo Individual Text</td>
<td>799* (431)</td>
<td>739* (440)</td>
</tr>
<tr>
<td>Group Photo Group Text</td>
<td>-1042** (450)</td>
<td>-1094** (459)</td>
</tr>
<tr>
<td>Donation in Past Year? (Recency)</td>
<td>1354*** (567)</td>
<td></td>
</tr>
<tr>
<td># Donations in 5 years (Frequency)</td>
<td>4274*** (153)</td>
<td></td>
</tr>
<tr>
<td>Total Donations in 5 Years (Monetary Value)</td>
<td>0.02*** (0.006)</td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>-34178*** (914)</td>
<td>-39429*** (1106)</td>
</tr>
</tbody>
</table>

Base Treatment is: Group Photo-Group Text Condition

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