NBER WORKING PAPER SERIES

SELF-SIGNALING AND PROSOCIAL BEHAVIOR:
A CAUSE MARKETING MOBILE FIELD EXPERIMENT

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Working Paper 21475
http://www.nber.org/papers/w21475

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
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August 2015

We are extremely grateful to Stefano Dellavigna and Emir Kamenica for extensive comments and suggestions. We are also grateful for comments from Michelle Andrews, Ron Borkovsky, Bart Bronnenberg, Alex Frankel, Xiliang Lin, Sanjog Misra, John List, Rik Pieters and Robert Sanders. We also benefited from the comments of seminar participants at the 2013 Colloquium on Big Data and Mobile at Temple University, Columbia University, HEC Paris, the 2015 NBER winter I.O. meetings, the Olin School of Business, Princeton University, the University of Alberta, the University of Houston, the University of Chicago, the University of Chicago Booth School of Business, the University of Wisconsin at Madison, and Wharton. The authors obtained IRB approval for the studies (IRB13-1400) from the University of Chicago Instutitional Review Board. Fang acknowledges research support from the National Natural Science Foundation of China [Grant 71172030, 71202138,71472130], the Youth Foundation for Humanities and Social Sciences of the Ministry of Education of China [Grant 12YJC630045, 14YJA630024,14YJC630166], and Sichuan University [Grant skqy201423,skqy201502]. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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JEL No. C7,C72,C9,C93,D03,D11,D12,D8,D81,M3,M30,M31

ABSTRACT

We empirically test an information economics based theory of social preferences in which ego utility and self-signaling can potentially crowd out the effect of consumption utility on choices. Two large-scale, randomized controlled field experiments involving a consumer good and charitable donations are conducted using a subject pool of actual consumers. We find that bundling relatively large charitable donations with a consumer good can generate non-monotonic regions of demand. Consumers also self-report significantly lower ratings of "feeling good about themselves" when a large donation is bundled with a large price discount for the good. The combined evidence supports the self-signaling theory whereby price discounts crowd out a consumer's self-inference of altruism from buying a good bundled with a charitable donation. Alternative theories of motivation crowding are unable to fit the non-monotonic moments in the data. A structural model of self-signaling is fit to the data to quantify the economic magnitude of ego utility and its role in driving consumer decisions.

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A randomized controlled trials registry entry is available at:
AEARCTR-0000799

1 Introduction

The study of prosocial behavior has spawned a large literature at the intersection of economics and psychology. Standard economic theory predicts that economic (e.g. monetary) incentives should increase an individual's willingness to perform an activity. Behavioral economists have puzzled over this conventional wisdom, at least since the controversial work by Titmuss (1971). Titmuss conjectured that paying blood donors would reduce their incentive to donate blood. Lacking hard evidence, the conjecture was initially dismissed by economists (Solow (1971); Arrow (1972); Bliss (1972)). Subsequently, a long literature in behavioral economics has generated a collection of empirical examples where economic incentives counter-intuitively reduce the supply of prosocial behavior (e.g. see the surveys in Frey and Jegen (2001) and Bowles and Polania-Reyes (2012)). A parallel literature in cognitive psychology has studied situations in which extrinsic (economic) incentives can crowd out an intinsically motivated individual's motivation to perform a task, the so-called *Hidden Costs of Reward* (Deci (1971); Lepper and Greene (1978)). However, the empirical evidence in the field for the crowding out effect of economic incentives on prosocial behavior has been mixed.[1]

The literature on social image and inference (e.g. Bernheim (1994)) offers one potential explanation for the inconsistent empirical findings of motivation crowding and prosocial behavior. Suppose that peers observe an individual's prosocial actions, but not her underlying preferences. An additional *reputational* motivation can influence prosocial behavior if the individual's actions generate informative signals to peers about her underlying motivation or status (Glazer and Konrad (1996); Benabou and Tirole (2006)). In this case, monetary rewards might weaken the social signal to peers of an individual's altruism, reducing the latter's incentive to behave prosocially for fear of appearing greedy or materialistic.

This paper explores a related reputational motivation driven by self-image, as opposed to social image. Using the analogy of interpersonal agency models, Bodner and Prelec (2002) and Prelec and Prelec (2010) study intrapersonal agency in a model of simultaneous "dual selves:" a decider who chooses an action and a judge who interprets the action[2]. The decider receives consumption utility from the action and the judge receives self-diagnostic "ego utility" from the interpretation of the action[3]. The model

[1] Kamenica (2012) and Gneezy, Meier, and Biel (2011) summarize the mixed evidence for motivation crowding out. Mellstrom and Johannesson (2008) fail to detect an overall effect of monetary incentives on blood donation. Lacetera, Macis, and Slonim (2009) not only find no evidence of crowding out, they also find that monetary incentives increase donation levels, albeit subject to cannibalization of other blood drives with lower incentives. Similarly, Ashraf, Bandiera, and Jack (2012) fail to detect crowding out effects from financial incentives in a study of Zambian hairdressers recruited to sell female condoms for an NGO. In other contexts, Gneezy and Rustichini (2000) find that rewards do crowd out school children's incentives to collect money for charity; and Frey and Oberholzer-Gee (1997) find crowding out effects for "not-in-my-backyard" projects such as locating a toxic waste dump near a municipality. Landry, Lange, List, Price, and Rupp (2010) find that small rewards crowd out charitable donations from prior donors, but increase donations of new donors. Barasch, Berman, and Small (2014) find that monetary incentives crowd out an individual's productivity in persuading others to behave prosocially.

[2] The model builds on the notion of brain modularity and dual-process decision-making (see Brocas and Carrillo (2014) for a survey).

[3] An alternative formulation of the dual-selves looks at the temporal conflict between the simultaneous myopic versus forward-looking selves (Thaler and Shefrin (1981); Fudenberg and Levine (2006)). A separate literature has looked instead at multi-period settings with a series of conflicting selves (e.g. Benabou and Tirole (2004); Bernheim and Thomadsen (2005)).

builds on the psychology of self-perception, which has long recognized that the individual can take the perspective of an outside observer and learn about herself by reflecting on her own actions (Bem (1972)). Self-signaling arises when the individual can influence her own self-beliefs through her actions. Benabou and Tirole (2006) explore the formal game theory of such self-signaling, modeling behavior and the corresponding self-signal as equilibrium outcomes in a game of incomplete information. In equilibrium, monetary incentives can be counterproductive by crowding out prosocial behavior when the incentive dampens the self-signal and reduces the ego utility.

We test self-signaling and crowding out by conducting two large-scale, controlled field experiments. We also measure the potential incompatibility between self-image motivation and extrinsic financial incentives to behave prosocially.[4] Like Gneezy, Gneezy, Riener, and Nelson (2012), we study consumer demand for a product with a prosocial characteristic. The experiments were conducted in a large Chinese city in collaboration with one of the world's largest mobile carriers. We randomly sampled subjects from a population of mobile subscribers who own a smartphone and live close to a movie theater. Each subject was randomly assigned to one of several promotional campaigns for a movie ticket, and was then contacted via SMS with the offer. One set of test cells consisted of "pure discounts" off the regular price of a ticket. A second set of cells consisted of "pure donations" of a pre-determined magnitude to a specific charity that would be made in conjunction with each ticket purchased. A third set of test cells consisted of a combination of a discount and a charitable donation. We observe each subject's purchase decision. In the second experiment, we also conducted a follow-up survey with a subset of the subjects twenty-four hours after the promotional experiments. We asked each subject a series of motivation-related questions. Since the receipt of the SMS message and the resulting purchase decision were all performed on an individual subject's smartphone, any signaling benefit would be private in nature.

The self-signaling theory generates several testable hypotheses. Under "pure discounts," we expect ticket demand to be monotonically increasing in the size of the discount since there is no self-signaling about altruism. The use of donations triggers the self-signaling motive. Discounts can dampen the signal, or warm-glow feeling, thereby reducing the diagnostic motivation to buy a ticket. If the dampening crowds out ticket purchases, we expect to observe regions of upward-sloping demand. As expected, in the absence of a donation, we find that discounts increase demand. When we combine discounts and donations, we find non-monotonicities that are consistent with the self-signaling theory. For relatively small donations, discounts increase demand. However, for even moderate-sized donations, we see a non-monotonic effect of discounts on ticket sales, which is consistent with a dampening of the self-signal. Our survey corroborates the self-signaling theory. At moderately high donation levels, subjects' self-reported purchase motivation to "feel good about themselves" declines with the level of the discount. Since the crowding out effect of discounts arises with large, not small discounts, we can rule out the "mere incidence of payment" effect whereby the crowding out arises at small (underpowered) reward levels

[4]Our work is similar to Pessemier, Bemmaor, and Hanssens (1977) who document survey evidence that monetary incentives generally reduce subjects' stated willingness to donate organs; although they do not attribute their findings to a specific psychological mechanism.

(Gneezy and Rustichini (2000); Frey and Jegen (2001)). We can also rule out a contextual inference whereby the consumer uses the promotion to learn about the movie quality and not to learn about herself (Benabou and Tirole (2003); Kamenica (2008)). Holding the total promotion budget fixed, crowding out arises from the allocation of the budget across discounts and donations, not from the total size of the budget.

We also use our experimentally-generated data to estimate the structural form of our model of demand, which nests the self-signaling equilibrium. This component of the paper contributes to the growing literature estimating parameter estimates from a completely specified model using field experiment data (Card, DellaVigna, and Malmendier (2011)). The estimator we use is robust to the potential multiplicity of equilibria that can emerge. Similar to DellaVigna, List, and Malmendier (2012), we use the structural estimates of consumer preferences to describe and quantify the underlying motivation. We find that the average consumption utility from donations is small and negative. In contrast, consumers place a statistically and economically significant positive weight on the perception of a high marginal utility from donations. At face value, the average consumer gets little consumption benefit from the charitable donation, but does value the self-perception of being altruistic. This finding is qualitatively similar to List (2006) who finds that, in the field, individuals are motivated by reputation and not by social preferences. Interestingly, consumers place significant positive weight on their perception of price sensitivity, suggesting they prefer not to appear motivated by low prices which is similar to the distaste for appearing greedy in Benabou and Tirole (2003).

Our work is closely related to the empirical literature studying self-deceptive behavior (Quattrone and Tversky (1984); Shafir and Tversky (1992); Mijovic-Prelec, Shin, Chabris, and Kosslyn (1994b); Dhar and Wertenbroch (2012); Gneezy, Gneezy, Riener, and Nelson (2012); Savary, Goldsmith, and Dhar (2014)). We contribute to this literature by testing self-signaling in the field and measuring its impact, through crowding out, on actual prosocial behavior.

Our work is also related to the empirical literature on social-signaling and prosocial behavior. List, Berrens, Bohara, and Kerkvliet (2004) find that social isolation moderates subjects' stated preferences over donations to a non-profit enterprise. Field experiments by Ariely, Bracha, and Meier (2009) and Ashraf, Bandiera, and Jack (2012) find that prosocial behavior increases dramatically when individual effort is displayed publicly, versus a control condition where effort remains private. In these studies, monetary incentives have a neutral effect in the public setting, but increase prosocial behavior in the private setting. Similarly, Berman, Levine, Barasch, and Small (2015) find that bragging about one's prosocial behavior increases peer perceptions when bragging provides novel information, but decreases peer's perceptions when the prosocial behavior is already publicly known. Our work contributes to this literature by providing field evidence of self-signaling and ego utility, a reputational motive for prosocial behavior that does not require social considerations.

The remainder of the paper is organized as follows. In section 2, we briefly discuss the theory and practice of cause marketing. Section 3 develops the model of self-signaling and the corresponding consumer demand, along with our key tests. Section 4 discusses the structure of the field experiments and the data. The estimator for the structural form of the model is discussed in section 6. Our empirical results are summarized in section 5. We conclude in section 7.

2 Cause Marketing

Our field experiments consist of cause marketing campaigns. A cause marketing campaign is "characterized by an offer from the firm to contribute a specified amount to a designated cause when customers engage in revenue-providing exchanges that satisfy organizational and individual objectives" (Varadarajan and Menon (1988)). Our cause marketing campaigns involve promotional offers for a movie ticket whereby the seller donates a pre-determined portion of the ticket price to a pre-determined charity. We also experiment with campaigns offering a discount off the regular price of a movie ticket as well as campaigns with both a donation and a discount.

In practice, cause marketing has become an increasingly popular marketing tactic in recent years, with total US spending increasing each year since at least 2005 and reaching $1.78 billion in 2009.[5] Conventional wisdom about cause marketing campaigns holds that consumer willingness-to-pay is increasing weakly in the donation size (e.g. Arora and Henderson (2007); Haruvy and Leszczyc (2009); Elfenbein and McManus (2010); Koschate-Fischer, Stefan, and Hoyer (2012)). Industry experts share this view, advising firms that more sponsorship raises consumer support. Cause marketing consultant Paul Jones explains that "Cause marketing works because people have an affinity for the cause or the cause's mission and want to support it.[6]" The underlying logic is that experts believe consumer response to cause marketing reflects altruism.

Our results are at odds with this conventional wisdom. We find that response to a cause marketing campaign is driven by the self-perception of altruism as opposed to genuine value for the cause itself. Our results indicate that willingness-to-pay does not unambiguously increase with the donation size. Rather, the combination of donations and discounts leads to regions of non-monotonicity in demand. In particular, for large discount levels, we find that larger donations may counter-intuitively reduce ticket demand. Based on these findings, a firm designing a cause marketing campaign should limit its use of non-complementary discount promotion tactics.

Our results are also at odds with the conventional wisdom of "integrated marketing communications" (e.g. Kotler and Keller (2011)), which generally views different marketing media as complementary and synergistic to one-another. Our findings suggest that discounts may be counter-productive when combined with donations.

[5] IEG Sponsorship Report, January 7, 2014, http://www.sponsorship.com/iegsr/2014/01/07/Sponsorship-Spending-Growth-Slows-In-North-America.aspx?utm_source=twitter&utm_medium=referral&utm_content=tweet&utm_campaign=iegsrTweet#.UtBkbmRDscJ.

[6] "Spending Dollars to Raise Pennies?" http://www.causemarketing.biz/2007/03/spending-dollars-to-raise-pennies/

3 A Model of Self-Signaling

3.1 Model

In this section, we develop a formal model of self-signaling, We adapt the models of Bodner and Prelec (2002) and Benabou and Tirole (2006) to our cause marketing campaign for movie tickets. In the model, a consumer receives a promotional offer (a, p) for a movie that includes a prosocial characteristic – a pre-determined donation amount to a charity – and a discount off the regular price. The consumer's consumption utility consists of the direct benefit from the movie ticket net of the price and, when applicable, the direct benefit from a charitable donation level. The direct benefit from a charitable donation may reflect genuine altruism and/or the joy of giving itself.[7] In addition, the consumer has a prior belief about her preferences before receiving the promotional offer. The consumer derives diagnostic "ego utility" based on her posterior self-beliefs after making her purchase decision in response to the promotional offer. The self-diagnostic component of utility captures the dual role of the *self* as an external observer who observes (or recollects) the purchase decision, but does not observe (or recollect) the underlying motivation (Bodner and Prelec (2002)). We model the *self* observer as a rational Bayesian learner who updates her self-beliefs based on the observed purchase behavior.[8] In the cause marketing setting, we assume that self-image reflects the perceived level of altruism (pure and/or impure) and the perceived level of price-sensitivity. During the cause marketing campaign, the consumer makes the utility-maximizing ticket purchase decision, which combines her consumption and diagnostic benefits.

Let V denote the consumer's value of the movie. Let $p > 0$ denote the ticket price and let $a \geq 0$ denote the monetary amount of the charitable donation bundled with a ticket. A consumer makes a discrete purchase decision $y \in \{0, 1\}$ where 1 denotes purchase and 0 denotes non-purchase.

The consumer's conditional indirect utility from buying and not buying are

$$U = \begin{cases} (V + \gamma a + \alpha p + \varepsilon_1) + R(a, p, \Lambda, 1) & , y = 1 \\ \\ R(a, p, \Lambda, 0) + \varepsilon_0 & , y = 0 \end{cases} \tag{1}$$

where $\Theta = (V, \alpha, \gamma)$ are consumption utility parameters, $\Lambda = (\lambda_\gamma, \lambda_\alpha)$ are ego utility parameters and ε_1 and ε_0 are a random utility shocks from buying and not buying a ticket respectively. The first utility component, $(V + \gamma a + \alpha p + \varepsilon_1)$, denotes the net consumption utility of the offer. The second term,

$$R(a, p, \Lambda, y) = \lambda_\gamma E(\gamma | a, p, y) + \lambda_\alpha E(\alpha | a, p, y) \tag{2}$$

denotes the consumer's ego utility (or diagnostic utility). One could think of this term as the self-esteem

[7]While our analysis will not attempt to distinguish between such pure and impure sources of altruism, Benabou and Tirole (2006) show how both may be captured by this specification.

[8]Bodner and Prelec (2002) discuss alternative, non-Bayesian learning and belief structures that we do not consider herein.

or "warm glow" feeling from the donation. The coefficients λ_γ and λ_α are the diagnostic utility weights on the consumer's posterior beliefs about γ and α respectively. The posterior expectations $E(\gamma|a,p,y)$ and $E(\alpha|a,p,y)$ are conditional on the observed features of the marketing campaign, (a,p), and the consumer's own observed action, y.[9]

Bodner and Prelec (2002) interpret the objective function (1) as a modular decision-making process. One component selects an action while the other component draws inferences from the action. It is not the objective of this paper to test or defend this dual-process paradigm. The "dual-process" approach to decision-making builds on a large and well-established literature that models the individual with conflicting objectives (see Brocas and Carrillo (2014) for a comprehensive literature survey)[10]. An alternative formulation might view the decision-maker as an inter-temporal sequence of *selves*, with the earlier selves adjusting behavior to manipulate the beliefs of the future selves (e.g. Benabou and Tirole (2004); Bernheim and Thomadsen (2005)). Our empirical analysis does not attempt to distinguish between the former modular view and the latter intrapersonal dynamic view.

The consumer purchases the ticket if

$$V+\gamma a+\alpha p+\Delta(a,p,\Lambda)+\varepsilon \quad > \quad 0 \tag{3}$$

where $\varepsilon=\varepsilon_1-\varepsilon_0$. The term $\Delta(a,p,\Lambda)=R(a,p,\Lambda,1)-R(a,p,\Lambda,0)$ captures the returns to ego utility from buying the ticket offer (a,p) versus not buying the ticket.

To complete the model, we denote the consumer's prior self beliefs before responding to the campaign as $F(\Theta,\varepsilon)$. We follow the convention in the demand estimation literature and let $\varepsilon\sim N(0,1)$, giving the classic random coefficients probit model of choice. The unconditional (expected) probability that the consumer purchases movie ticket offer (a,p) is:

$$Pr(y=1|a,p) \quad = \int\Phi(V+\gamma a+\alpha p+\Delta(a,p,\Lambda))\,dF(\Theta) \tag{4}$$

where $\Phi(\bullet)$ is the CDF of a standard Normal distribution.

A complication in the calculation of the choice probability (4) is that it nests the ego returns to buying the ticket, $\Delta(a,p,\Lambda)$. We assume the consumer uses Bayes' rule to update her self-beliefs. For a given offer (a,p), the consumer's posterior self beliefs must satisfy:

$$E\left(\Theta_j|a,p,y\right)=\begin{cases}\frac{\int\Theta_j\Phi(V+\gamma a+\alpha p+\Delta(a,p,\Lambda))dF(\Theta)}{\int\Phi(V+\gamma a+\alpha p+\Delta(a,p,\Lambda))dF(\Theta)}, & y=1\\ \\ \frac{\int\Theta_j[1-\Phi(V+\gamma a+\alpha p+\Delta(a,p,\Lambda))]dF(\Theta)}{\int[1-\Phi(V+\gamma a+\alpha p+\Delta(a,p,\Lambda))]dF(\Theta)}, & y=0\end{cases} \tag{5}$$

[9]See Köszegi (2006) and Mobius, Niederle, and Niehaus (2014) for related models in which decisions are driven, in part, by ego utility.

[10]A seemingly paradoxical aspect of the theory is that the individual possesses two conflicting beliefs. The neuroscience literature has provided compelling empirical evidence where a single individual response conveys conflicting beliefs (e.g. Mijovic-Prelec, Shin, Chabris, and Kosslyn (1994a)).

where $j \in \{V, \gamma, \alpha\}$. For estimation, we will specify a parametric distribution $F(\Theta)$ so that we can solve the system of posterior beliefs 5 numerically. In section 6.3 below, we use the structural parameter estimates from section 6.2 to explore the potential for a multiplicity of equilibrium beliefs to correspond to a given promotional offer (a, p).

Crowding out arises when the loss in ego utility overwhelms any consumption utility gains from a marketing promotion. Consider two offers (a_0, p_0) and (a_0, p_1). As we lower the price to p_1, consumption utility increases by the amount $\alpha(p_1 - p_0)$. However, the price discount also changes the returns to ego utility by the amount $\Delta(a_0, p_1, \Lambda) - \Delta(a_0, p_0, \Lambda)$. Demand decreases overall if $\alpha(p_1 - p_0) < \Delta(a_0, p_1, \Lambda) - \Delta(a_0, p_0, \Lambda)$. In section 6.3 below, we use the structural parameter estimates from section 6.2 to explore crowding out behavior in cases where the ego utility change exceeds the consumption utility change.

3.2 Alternative Explanations

Past work has discussed alternative mechanisms that could also lead to a crowding out of motivation and, hence, of prosocial behavior. Frey and Jegen (2001) derive motivation crowding from the "mere incidence of payment." Suppose an individual's intrinsic motivation is suppressed when monetary incentives are introduced. That is, the extrinsic motivation replaces the intrinsic motivation. An individual's willingness to supply prosocial behavior would be discontinuous in the level of monetary incentives at the origin. As a result, a low-powered incentive could crowd out prosocial behavior if the corresponding extrinsic motivation is weaker than the intrinsic motivation. Gneezy and Rustichini (2000) provide empirical evidence of such crowding out from small, *low-powered* rewards. They also find that a considerable amount needs to be paid before subjects supply the same level of prosocial behavior as in the base case where they work for free.[11] This discontinuous shift could also be consistent with a self-perception theory like the one we investigate. To construct a test between a "mere incidence of payment" theory and self-signaling, we exploit the fact that under self-signaling, crowding out need not arise as a discontinuity at very small reward levels per se. Rather, we may observe non-monotonicity in the effect of a reward whereby small rewards increase demand and larger rewards reduce demand. A direct test can also be constructed by surveying consumers about their warm-glow feeling under different promotional settings.

Benabou and Tirole (2003) derive motivation crowding from a theory of "contextual inference," whereby the consumer learns about the task itself rather than about herself. In our experiments, a consumer may interpret a promotion as an ex ante signal about the underlying quality of the movie, with an aggressive promotion signaling low quality. This type of ex ante learning is in fact closer in spirit to the context effects studied in Kamenica (2008), as opposed to motivation crowding. Such ex ante learning about the product before purchasing differs from most of the past empirical work on product uncertainty where consumers learn ex post through their consumption experiences after the purchase (Erdem and Keane (1996); Ackerberg (2003); Crawford and Shum (2005)). To control for contextual

[11] Kamenica (2012) summarizes other experimental evidence that small rewards can be counterproductive.

inference, we assume the consumer's quality inference is based on the total amount the firm spends on the promotion (discount plus donation). We then construct test cells that manipulate the allocation of the promotion budget to discount and donation, holding the total amount fixed. We also include a cell with an extremely large "pure discount" that exceeds the promotional budget of any of our campaigns that combine discounts and donations. We do not expect the large discount to crowd out demand under self-signaling. A direct test can also be constructed by surveying consumers on their perception of the movie in different promotional settings. In theory, we would need to write down a model describing the full equilibrium between firms and consumers. The quality signal inferred by consumers would then reflect their beliefs about the firm's incentives to offer discounts and donations. This is however beyond the scope of the experiments we conduct.

Consumers could also form a contextual inference about the charity itself. This alternative is more difficult to rule out with purchase behavior since donation levels can also dampen the self-signal. A more direct test can be constructed by surveying consumers on their perception of the charity in different promotional settings.

4 Data

To test the self-signaling theory, we conducted two randomized field experiments. In the first experiment, we focused on testing the conventional result whereby crowding out arises for small rewards, the "mere incidence of payment." In our second experiment, we explore larger donation and discount sizes to explore our proposed theory based on signal-dampening, which can generate crowding out at larger reward levels.

4.1 Study 1

This field experiment was conducted with a corporate partner that is one of the largest wireless service providers in the world. The wireless provider selected the off-season period for this promotion to avoid a blockbuster effect in the movie voucher. Most blockbusters had been released immediately before and just after Christmas of 2013. The regular price of a 2D movie during our sample period is 60 RMB.

Our experimental context consisted of a mobile SMS offer for a general admission voucher for any 2D movie showing between January 15, 2014 and January 31, 2014. The offer was pushed to subjects' smartphones on January 15, 2014 and the offer expired on January 16, 2014. Recipients purchased movie tickets by clicking a link embedded in the SMS ad. If a user purchased a ticket, the cost was immediately charged to her monthly phone bill. Both the promotional offer and the purchase decision were conducted on an individual subject's phone, creating a private signaling benefit.

Subjects were randomly assigned to one of several promotional conditions.[12] In the baseline, control

[12]We used the three-step approach of Deng and Graz (2002) to construct our sample. First, we used the RANUNI function in SAS to assign a unique random uniform number to each user. Second, we sorted all random numbers in sequence. Third,

condition, the mobile ad SMS read: "To buy a voucher for general admission to any of the 2D showings in January with your mobile phone, the purchase link below is valid until January 16..." In the pure discount condition, the SMS read: "To buy a voucher for general admission to any of the 2D showings in January with your mobile phone at a [3, 6, 15, 30, and 36 RMB] discount, the link below is valid until January 16..." Subjects in this condition were randomly assigned to one of the 5 discount levels. In our pure donation condition, the SMS read: "To buy a voucher for general admission to any of the 2D showings in January with your mobile phone, [wireless provider's name] will donate [3, 6, 15, 30, and 36 RMB] per each sold ticket to poor elderly people, the purchase link below is valid until January 16..." Subjects in this condition were randomly assigned to one of the 5 donation levels. Finally, in our combined discount and donation condition, the SMS read: "To buy a voucher for general admission to any of the 2D showings in January with your mobile phone at a [3, 6, 15, 30, and 36 RMB] discount, [wireless provider's name] will donate [3, 6, 15, 30, and 36 RMB] per each sold ticket to poor elderly people, the purchase link below is valid until January 16..." Subjects in this condition were randomly assigned to one of the following ten offers (discount,donation): (3,3), (3,6), (3,15), (3,30), (6,3), (6,6), (6,15), (15,3), (15,6), (30,3).

To construct our experimental sample, we begin with the 15 million subscribers in a large city. From this population, we focus on those mobile subscribers living within 2 kilometers of one of the theaters playing the movie. By conditioning on proximity to the theater, we expected to reduce noise associated with heterogeneity in taste based on geographic proximity to a theater. Given the urban location of the theaters, we therefore target our analysis to subscribers with an urban home address. We also conditioned on the sub-population of subscribers that had purchased a movie ticket using their smartphone during the previous 6 months. This condition ensured that the subscriber had a smartphone (i.e. that could be used to purchase a movie ticket) and that the subscriber had potential interest in a mobile purchase offer. From this overall target population of 1 million, we randomly sampled 10,500 mobile subscribers to whom the wireless provider pushed one of our promotional SMS messages.

Our final experimental sample consists of a 25-cell, between-subjects design. Table 1 summarizes the experimental design and the sample sizes in each cell. In total, 273 of our 10,500 subscribers who received one of our SMS messages purchased a movie ticket through their smartphone. This 2.6% purchase rate is quite high for a mobile promotion in comparison with the 0.3% to 0.6% click-through response rates for internet targeting (Cho and Cheon 2004).

4.2 Study 2

This field experiment was conducted with the same corporate partner as Study 1. We coordinated the experiment with the Chinese release of the movie *X-Men: Days of Future Past*, on May 23, 2014 in IMAX theaters. This movie was selected since the blockbuster potential would guarantee a reasonably

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we we extracted a sample from the sorted population. This three-step algorithm was integrated into the wireless provider's IT system.

high baseline rate of interest in tickets, giving us sufficient statistical power. The movie was released only in a 3D version, with a regular ticket price of 100 RMB.

Our experimental context consisted of a mobile SMS offer for a general 3D movie admission voucher that could be redeemed for any showing of the X-Men movie at any future date. The offer was pushed through to subjects' smartphones on May 21,2014 and the offer expired on May 22, 2014. The average respondent purchased a ticket 6.9 hours after receiving the offer, conditional on purchase. Recipients purchased movie tickets by clicking through a link embedded in the SMS ad. If a user purchased a ticket, the cost was immediately charged to her monthly phone bill. Both the promotional offer and the purchase decision are conducted on an individual subject's phone, creating a purely private signaling benefit.

Subjects were randomly assigned to one of several promotional conditions. In the baseline control condition, the mobile ad SMS read: "To buy a voucher for general admission to any of X-Men: Days of Future Past's 3D showings, follow this link..." In the pure discount condition, the SMS read: "To buy a voucher for general admission to any of X-Men: Days of Future Past's 3D showings at a [20, 35, 50, 60, 75 RMB] discount, follow this link..." Subjects in this condition were randomly assigned to one of the 5 discount levels. In our pure donation condition, the SMS read: "To buy a voucher for general admission to any of X-Men: Days of Future Past's 3D showings, [wireless provider's name] will donate [5, 10, 15 RMB] per each ticket sold to poor elderly people, follow this link..." Subjects in this condition were randomly assigned to one of the 3 donation levels. Finally, in our combined discount and donation condition, the SMS read: "To buy a voucher for general admission to any of X-Men: Days of Future Past's 3D showings at a [20, 35, 50, 60 RMB] discount, [wireless provider's name] will donate [5, 10, 15 RMB] per each sold ticket to poor elderly people, follow this link..." Subjects in this condition were randomly assigned to one of the 4 discount levels and one of the 3 donation levels.

To construct our experimental sample, we followed the same template as in Study 1. Using the same target population of 1 million, we randomly sampled 30,300 mobile subscribers to whom the wireless provider pushed one of our promotional SMS messages. These subjects did not overlap with those from Study 1.

Our final experimental sample consists of a 5 (discount: 0, 20, 35, 50, 60 RMB) $\times$ 4 (donation: 0, 5, 10, 15 RMB per ticket sold) between-subjects design. We also included an additional condition with a 75 RMB discount and no donation. The comparison of this condition to a cell with a 60 RMB discount and 15 RMB donation allows us to test for a contextual inference effect. In total, we have 21 groups in this experiment. We over-sampled certain cells to ensure sufficient statistical power to test for non-monotonicity associated with crowding out. Table 2 summarizes the experimental design and the sample sizes in each cell.

Although Chinese regulation prevents us from accessing the mobile subscribers' demographic information, we were able to obtain the following mobile usage behavior. For each subject, we observe the average revenue per month (ARPU), the average number of voice minutes used per month (MOU), the average number of short message service (SMS) messages sent and received per month, and the average general packet radio service (GPRS) per month to measure the volume of data usage. Table 3 summarizes this usage behavior.

Table 3 also shows that 694 of our 30,300 subscribers who received one of our SMS messages purchased a movie ticket through their smartphone. This 2.29% purchase rate is consistent with the results of the first study.

Finally, on May 23, 2014, the day after the SMS expired, we conducted a follow-up telephone survey. For each of 12 of our 21 experimental cells, we randomly sub-sampled 40 of our subjects who purchased a ticket and 40 of our subjects who did not purchase a ticket. Each of the "not purchased" subjects was presented with the survey in Figure 3, consisting of 8 questions. An analogous survey was presented to "purchased" subjects, as in Figure 4. Response rates are summarized in Table 4. Response rates varied from 23 to 35 across the cells.

5 Experimental Results

In this section, we test elements of our self-signaling model using the raw experimental data. In this way we can document evidence in favor of the self-signaling theory without relying too heavily on stylized modeling assumptions from section 3.

5.1 Experimental Data for Study 1

Study 1 explores the impact of small rewards on consumer motivation to support charity through their ticket purchase. We tabulate our experimental data in Table 5. Recall that the regular price for this type of movie voucher is 75 RMB. Surprisingly, no subjects buy in our base case with no promotional offer; although given the discrete nature of our data, we cannot rule out a purchase probability of as high as 0.007% at the 5% significance level.[13] We observe positive and significant effects from "pure discounts" on demand for discounts of 15 RMB or larger. Demand increases by nearly 3 percentage points when the discount is increased from 15 RMB to 30 RMB ($p<.02$); although we do not find a significant difference in demand between a discount of 30 RMB and 36 RMB. We also observe a positive and significant effect from "pure donations" of at least 30 RMB. When we combine discounts and donations, all of our point estimates are monotonically increasing in the level of discounts. For instance, at a donation level of 3 RMB, increasing the discount from 3 RMB to 30 RMB increases demand by over two percentage points ($p<.02$). However, at higher donation levels, the marginal effect of a discount does appear to decrease. At a discount level of 30 RMB, we see demand decrease by almost two percentage points when the donation increased from 0 RMB to 3 RMB ($p<0.06$). This is mild evidence of signal dampening. But, the decline is not very precise and, at a 5% significance level, we cannot rule out a demand increase of half a percentage point. Interestingly, when the discount is low (3 RMB off the regular price) we find a monotonically increasing effect of the charitable donation level on demand. Doubling the donation

[13]We use the "cii" function in STATA.

from 15 to 30 RMB more than doubles demand, in contrast with the finding of a flat effect of charitable donation size documented in Karlan and List (2007).

In Study 1, we see no evidence of the *mere incidence of payments* effect. In some of our campaigns, small discounts as low as 3 RMB increase demand. Comparing no donation (i.e. pure discounts) to a donation level of 3 RMB, small discounts appear to work better in the latter than the former case. However, it is the larger (higher-powered) discounts (15 and 30 RMB) that appear less effective when combined with a 3 RMB donation.

5.2 Experimental Data for Study 2

We tabulate our experimental data in Table 6. Recall that the regular price for this type of movie voucher is 100 RMB. No subjects buy in our base case with with the regular price level and no donation offer; although given the discrete nature of our data, we cannot rule out a purchase probability of as high as 0.526% at the 5% significance level. The average differences in purchase rates are increasing in donation and discount levels respectively; although some of the increases are insignificant at conventional levels. Increasing the donation from 0 RMB to 5 RMB increases the purchase probability by 0.429% ($p<0.05$);[14] from 5 RMB to 10 RMB increases the purchase probability by 0.143% ($p<.35$); and from 10 RMB to 15 RMB increases the purchase probability by 0.571% ($p<0.13$). Raising the discount from 0 RMB to 20 RMB increases the purchase probability by 0.714% ($p<0.02$); from 20 RMB to 35 RMB increases the purchase probability by 2.57% ($p<0.01$); from 35 RMB to 50 RMB increases the purchase probability by 2.23% ($p<0.02$); from 50 RMB to 60 RMB increases the purchase probability by 4.29% ($p<0.36$); and from 60 RMB to 75 RMB increases the purchase probability by 2.86% ($p<0.42$).

We plot the purchase frequencies for each promotional condition in Figure 1. Results are presented by donation level. All of our discount levels generate a positive and statistically significant lift in purchase probability relative to the baseline case of no discount. However, it is not always the case that a larger discount increases demand. Consider the promotion conditions with a donation level of 10 RMB. Increasing the discount from 0 RMB to 20 RMB increases the purchase probability by 1.42 percentage points ($p<0.01$). Similarly, increasing the discount from 20 RMB to 35 RMB increases the purchase probability by 0.7 percentage points ($p<0.12$); although here we cannot rule out "no change" at the 5% significance level. However, if we increase the discount from 35 RMB to 50 RMB, the purchase probability falls 0.9 percentage points ($p<0.01$). If we consider a donation level of 15 RMB, increasing the discount from 35 RMB to 50 RMB reduces the purchase probability by 0.7 percentage points ($p<0.025$). This non-monotonicity in the effect of price on demand is consistent with our theory of self-signaling.

The line plot in Figure 2 makes it easier to compare relative magnitudes of the promotional conditions. The plot illustrates the negative complementarity between the two promotion formats, discounts and donations, on purchase behavior. In addition to the non-monotonicity in the price effect, we also see how price discounts moderate the effectiveness of a charitable donation. For low discount levels of

[14] We use the "prtest" routine in STATA to compare differences in sample proportions.

0 RMB or 20 RMB, a small charitable donation (5 RMB versus 0 RMB) increases the purchase probability. However, once the discount is 35 RMB or higher, the rank order of donation effects flips – higher donations decrease the purchase probability. This negative moderating effect of discount levels on the marginal effect of a small donation is also consistent with our theory of self-signaling.

Figure 2 also shows that the crowding out of demand is not simply a "mere incidence of payment" effect. For high donation levels, small discounts in fact increase demand and the discount only becomes counter-productive at larger levels of 50% off or more.

A potential concern is that the crowding out reflects contextual inference about the quality of the movie itself. A large promotion could convey negative information about the quality of the movie. To rule this out, we note that prosocial motivation is only triggered in the presence of a donation. In contrast, contextual learning can arise even under pure discounts. So we can test between the two theories by taking specific pure discount scenarios in Table 6 and comparing them to combinations of discounts and donations that generate the same-sized promotional budget. Given that demand is more sensitive to discounts than to donations, we would expect contextual inference to be stronger when the promotional budget is entirely allocated to a discount. Consider the comparison of a promotional budget of 35 RMB with a budget of 60 RMB. If we compare a pure discount of 35 RMB to a pure discount of 60 RMB, demand increases by 2.7 percentage points ($p<.01$). If we compare instead a pure discount of 35 RMB to a combination of a discount of 50 RMB and a donation of 10 RMB, we observe crowding out as demand falls 1.5 percentage points ($p<.01$). In fact, a pure discount of 75 RMB has a positive effect on demand whereas crowding out can arise with smaller overall promotion budgets that combine discounts and donations.

In our setting, there is no obvious way to construct a direct test of self-signaling that manipulates whether or not a consumer has a reputational motivation (e.g. List (2006)). Instead, we use the survey. Recall that survey respondents were sampled from the set of subjects used in the ticket promotion experiment the previous day. For most of the questions, we find little statistical differences in responses across test cells. However, we do find differences in responses to question 3 (iv) where we asked respondents to rate on an 11-point scale the extent to which they agree that a purchaser of a ticket in a given test condition "...wanted to feel good about yourself by donating to the charity." This question was intended to capture the self-signaling (i.e. warm-glow feeling) from the purchase. Figure 5 plots the purchase behavior in each of our experimental cells. For those cells with survey respondents, we also plot the corresponding mean self-reported warm glow level. Consistent with our theory, we see the warm glow changing very little across discount conditions when donation levels are low. But, large discounts reduce the warm glow a lot when donations are relatively high. The decline in warm glow is significant. The mean *warm glow* rating falls from 9.85 (15 RMB donation, 35 RMB discount) to 5.41 (15 RMB donation, 60 RMB discount). The F-stat between these two cells is 132.38, so we easily reject the null of equal means.[15] As further evidence of self-signaling, as opposed to social signaling, an average of 1.7

[15] Re-running the same test using an ordered logit to capture the discreteness of our outcome variable, we still easily reject the null of equal mean effects with a Chi-Square test statistic of 36.01.

tickets were sold conditional on purchase, indicating that many respondents purchased a single ticket.

In appendix B, we report results from some of the other survey questions. For instance, we asked subjects to rate the statement "the discount was big enough to make it worthwhile for your to buy a movie ticket." Figure 10 shows that self-reported price sensitivity increases with the size of the discount. However, consistent with our signaling theory, the magnitude of the ratings and the magnitude of the increase in ratings as the discount increases is smaller for higher donation levels. That is, higher donations weaken the role of discounts on purchase behavior.

We can also test contextual inference about the quality of the movie. Subjects were asked to rate the statement "You wanted to watch the movie ..." on an 11-point scale. Unlike the self-reported warm-glow and price-sensitivity levels, the movie preference in Figure 11 is flat across price conditions with an average response of 8.76. However, the mean rating does fall slightly as the charitable donation increases. The mean rating falls from 10.1 (5 RMB donation, 20 RMB discount) to 8.4 (15 RMB donation, 20 RMB discount), with an F-stat of 24.89. A limitation of this question is that it might simply reflect the mean movie taste, V, for inframarginal consumers as opposed to the mean perception of the movie quality. We construct an analogous test for contextual inference about the charity. Subjects were asked to rate the statement: "You valued the charity and wanted to support it" on an 11-point scale. Figure 12 shows the same flat pattern across promotional conditions, with an average rating of 9.28.

The survey also indicates that the subjects considered the charity itself to be legitimate and worthy. Over 80 percent of respondents gave a response of at least 8 out of 11, and all of the responses were above 5. The results also indicate that subjects took the survey itself seriously and deliberated over their responses. In contrast with the rating of the charity, when asked "Will you continue donating money to this charity in the future?" the average score was 7.99, with only 44% of subjects giving scores of 7 or less, with some as low as 1. Mean responses are reported in Figure 13. We also asked subjects to rate the statement "Does this SMS deal seem too good to be true for you?" All the responses were over 7, but there was almost no difference in responses across cells (mean ranged from 9.6 to 10.4). This evidence is consistent with subjects' not inferring a negative quality signal about the movie in response to a larger discount and/or donation combination. Similarly, subjects did score the statement "Do you think this purchase is an impulse buy?" quite low, with a mean of less than 5 across all cells, including those with discounts of 50% or more off the regular price.

6 Model Estimation

6.1 An MPEC Estimator

To quantify the implications of self-signaling, we develop an estimator in this section to estimate the underlying structural form of the model from section 3 using our experimental data setting. Let $h = 1,...,H$ denote individual subjects in the experiment. Each subject is randomly assigned to one of $t = 1,...,T$ promotion conditions, (a_t, p_t). Each subject then makes a choice $y^h \in \{0,1\}$. We assume rational expectations in the sense that all subjects have the same prior self beliefs and these beliefs coincide with the true population distribution of tastes. Recall that the expected probability that consumer h who is assigned to promotion condition t purchases a movie ticket is:

$$Pr\left(y^h = 1|a_t, p_t\right) \quad = \int \Phi\left(V + \gamma a_t + \alpha p_t + \Delta\left(a_t, p_t, \Lambda\right)\right) dF\left(\Theta\right) \ . \tag{6}$$

For our baseline specification, we use a discrete approximation, $F(\Theta) = \begin{cases} \Theta^1, & \omega \\ \Theta^2, & 1-\omega \end{cases}$, giving the following choice probability:

$$Pr\left(y^h = 1|a_t, p_t\right) \quad = \sum_{k=1}^{2} \Phi\left(V^k + \gamma^k a_t + \alpha^k p_t + \Delta\left(a_t, p_t, \Lambda\right)\right) \omega^k \ .$$

We now discuss an estimator of the structural parameters of the model in section 3. The potential multiplicity of self-signaling equilibria for the model raises the well-known coherency problem with maximum likelihood estimation (Tamer (2003)). We use the constrained optimization approach proposed in Su and Judd (2012) to obtain consistent, maximum likelihood estimates.

To simplify the model, let $\Gamma = (\Theta, \Lambda)$ denote all the structural parameters. Our MPEC estimator maximizes the following objective function:

$$\ell\left(\Gamma, \delta\right) = \sum_h \left(y^h ln\left(Pr\left(y^h = 1|a_t, p_t; \Gamma, \delta_t\right)\right) + \left(1 - y^h\right) ln\left(1 - Pr\left(y^h = 1|a_t, p_t; \Gamma, \delta_t\right)\right)\right) \tag{7}$$

subject to the constraints

$$\begin{aligned} \delta_{n1t} &= \frac{\sum_k \Theta_n^k \Phi\left(V^k + \gamma a_t + \alpha p_t + \Delta\left(a_t, p_t, \Lambda\right)\right)\omega^k}{\sum_k \Phi\left(V^k + \gamma a_t + \alpha p_t + \Delta\left(a_t, p_t, \Lambda\right)\right)\omega^k} \quad , t = 1, .., T \\ \delta_{n2t} &= \frac{\sum_k \Theta_n^k \left[1 - \Phi\left(V^k + \gamma a_t + \alpha p_t + \Delta\left(a_t, p_t, \Lambda\right)\right)\right]\omega^k}{\sum_k \left[1 - \Phi\left(V^k + \gamma a_t + \alpha p_t + \Delta\left(a_t, p_t, \Lambda\right)\right)\right]\omega^k} \end{aligned} \tag{8}$$

where

$$Pr\left(y^h = 1|p_t, a_t; \Gamma, \delta_t\right) = \sum_k \Phi\left(V^k + \gamma a_t + \alpha p_t + \Delta\left(a_t, p_t, \Lambda\right)\right) \omega^k$$

and

$$\Delta\left(a_t, p_t, \Lambda\right) = \lambda_\gamma \left(\delta_{\gamma 1t} - \delta_{\gamma 2t}\right) + \lambda_\alpha \left(\delta_{\alpha 1t} - \delta_{\alpha 2t}\right).$$

We also experiment with a Normal distribution of heterogeneity, $F(\Theta) = N\left(\bar{\Theta}, \Sigma_\Theta\right)$. Details on the formulation of the corresponding MPEC estimator are available from the authors upon request.

The constraints, (8), ensure that our estimated ticket purchase probabilities are exactly consistent with the self-signaling equilibrium implied by Bayes' rule, where δ_t are the equilibrium beliefs corresponding to a given promotion state (a_t, p_t). This formulation yields an objective function that is smooth in the equilibrium beliefs, δ_t. In contrast, a nested fixed-point approach that re-computes the equilibrium beliefs exactly at each iteration of the parameter search over Γ would produce an objective function that is potentially discontinuous in the structural parameters. Another advantage of the MPEC approach is that we do not need to solve repeatedly for all the equilibria for each step of the parameter search. Su (2014) demonstrates that the objective function (7) is equivalent to integrating the objective function over a probability distribution for the countable set of potential equilibria to the model and where the probability is deterministically equal to one for the equilibrium with the highest likelihood. If we also assume that the same equilibrium is always played in a given promotion state, (a_t, p_t) then our MPEC estimates of Γ are equivalent to the maximum likelihood estimates.

The identification of most of the model parameters follows from the usual econometric theory for discrete choice models estimated with cross-sectional data. Bajari, Fox, and Ryan (2007) establish the nonparametric identification of the random coefficients distribution, Σ, for discrete choice models with linear indirect utility. The diagnostic weights, λ_γ and λ_α, are then identified parametrically from the observed non-monotonic moments in our purchase data. These moments would not be fit by conventional choice models.

6.2 Structural Estimates

Our three key models consist of the baseline probit, the random coefficients probit, and the random coefficients probit with self-signaling. Table 7 reports the structural parameter estimates of the three models, including three variants of the self-signaling specification. Our self-signaling specifications consists of: (1) self-signaling on the taste for donations, γ; (2) self-signaling on the taste for donations, γ, and the price sensitivity, α; and (3) self-signaling on the taste for donations, γ, and the taste for movies, V. In each of the random coefficients and self-signaling specifications, we use two mass points to approximate the distribution of heterogeneity.

The empirical results indicate that adding heterogeneity improves fit substantially, as seen by comparing columns one and two. The mixing probability in column two is 0.98, but is nevertheless significantly different from 1. A standard likelihood ratio test to compare the model with one versus two mass points is not well-defined since the restricted model (standard probit) sets the mixing probability to $\omega = 1$, which is on the boundary. However, we can see a substantial improvement in the Akaike Information Criterion (final row of Table 7), which includes a penalty for a model with more parameters.

The probit and random coefficients probit models are straw men since we know a priori that neither can predict the non-monotonic effect of prices in the data. As expected, the self-signaling models in columns three to five fit the data better than the random coefficients probit. The best-fitting model has self-signaling on both donation taste and price sensitivity. The diagnostic weights, λ_γ and λ_α are both statistically significant. We easily reject the random coefficients probit model against the alternative model with self-signaling on both donations and prices using the likelihood ration test at conventional significance levels ($LR = 23.27$). We also reject the self-signaling on donations only ($\lambda_\alpha = 0$) against the alternative model with self-signaling on both donations and prices ($LR = 9.15$). Comparing the nonnested specifications with self-signaling on donations and price versus self-signaling on donations and movies, we select the former specification using the Akaike Information Criterion.

Our best-fitting model with self-signaling on γ and α is able to fit the non-monotonic moments in our data in spite of having only two additional parameters than the baseline random coefficients probit. We show this fit in Figure 6. In the first column of panels, we show in red the observed average choice behavior in each of the experimental cells, where each row corresponds to the different donation levels. In the second column, we show in blue the corresponding predicted choice behavior from the random coefficients probit. In the third column, we show in magenta the predicted choice behavior from the random coefficients probit with self-signaling on γ only. In the bottom two panels, this model predicts flatter demand as we lower the price level in comparison with the baseline random coefficients probit. But it does not fit the non-monotonicity. In the fourth column, we show in black the predicted choice behavior from the random coefficients probit with self-signaling on γ and on α. In the bottom two panels, we see how the self-signaling model is able to fit the non-monotonic relationship between price and choice rates when the donation levels are relatively high. Finally, in the fifth column, we show in green the predicted choice behavior from the random coefficients probit with self-signaling on γ and on V. This model is not able to fit the non-monotonicity in observed choice behavior.

Some of our self-signaling specifications fail to capture the non-monotonicity in demand. First note that in all of our self-signaling specifications, we find a very large segment that is less price-sensitive (higher α) than the smaller segment, but with lower taste for movies, V, and donations, γ. For the specification with self-signaling on γ only, the parameter values imply that it is very hard to send a strong positive signal about γ since only the smaller segment (comp 2) has a positive, albeit small, marginal consumption utility for γ. Choices in this specification are mostly driven by consumption utility and not by ego utility. So as prices fall, the larger segment is motivated to buy a ticket, which worsens the posterior inference on γ. But, the change in signal is not large enough to deter buyers. Furthermore, larger donation levels actually deter the larger segment from buying, which means that larger donation levels actually improve the self-signal on γ in this case. The net effect is that raising the donation and lowering the price has a relatively flat effect on demand (as in Figure 6), but does not create a non-monotonicity. Allowing for self-signaling on both γ and V does not improve fit since γ and V are positively correlated across the two segments. Hence, there is little improvement in the ability to manipulate the signal.

In contrast, allowing for self-signaling on both γ and α improves fit since γ and α are negatively correlated across the segments. Consider high donation levels of $a = 15$. As we lower the price, we draw in more of the smaller segment consumers, which means the posterior signal on γ improves whereas the posterior on α worsens. At low enough prices, the latter effect dominates and demand actually falls.

For the remainder of our analysis, we will focus on the best-fitting specification with discrete heterogeneity and self-signaling on γ and α. The structural coefficient estimates, Γ, in the fourth column of Table 7 provide substantive implications about prosocial behavior in our ticket-buying context. The heterogeneity distribution mixes over two mass points of tastes and while one point has 98% of the probability mass, the amount of mass on the remaining segment is statistically different from zero. If we interpret each mass point as a consumer "type," then both types of consumers have negative price sensitivity, α. So, as one might expect, demand slopes downwards in the absence of self-signaling. The sensitivity to donations, γ, is positive but statistically insignificant for both types of consumers. Interestingly, the larger segment (98%) has a negative and statistically significant taste for movies. More interesting are the large and statistically significant positive diagnostic weights, λ_γ and λ_α. Taken at face value, consumers prefer the self-image of getting consumption utility from donations, $\lambda_\alpha > 0$. They also value the self-image of being relatively price-insensitive, $\lambda_\alpha > 0$. These findings are consistent with the formulation in Benabou and Tirole (2006) whereby consumers want to appear to value charity while not appearing to be driven by "greed" (in this case low prices).

Although not reported herein, we also estimated the self-signaling models using a Normal distribution of taste heterogeneity. Using the Akaike Information Criterion to assess relative model fit, we found that the Normal distribution did not fit the data nearly as well as our finite mixture specifications reported above. This is perhaps not surprising since the non-monotonicity in demand plays an important role in identifying the heterogeneity. The symmetry and thin-tailed features of a Normal distribution may limit its ability to fit our data.

6.3 Crowding Out and Multiplicity

In this section, we illustrate how prices and donations moderate individual choice behavior under self-signaling. We also illustrate the potential multiplicity of equilibria. Our analysis focuses on the estimated model parameters from the specification with self-signaling on γ and α, our best-fitting model from the previous section.

In our model, the demand correspondence is an equilibrium outcome of the self-signaling game. We derive demand by numerically computing the equilibrium beliefs and choice behavior over a grid of $27,217$ pairs of donation and price levels: $a \in [1,16]$ and $p \in [20,100]$. For each grid point, we compute an equilibrium for each of $1,000$ independent random starting values. A concern is that certain solution paths might be difficult to locate numerically. The smoothness and regularity of the model rules out equilibria that are isolated or contain continua of equilibria or branching points (see for instance Borkovsky, Doraszelski, and Kryukov (2008)).[16] The equilibrium demand correspondences plotted in Figure 7 are consistent with the regularity of the model. The lack of gaps in the plotted solution paths makes it unlikely that we are failing to locate entire equilibrium paths since this would require us systematically to find points on one path as opposed to another[17].

Figure 7 also illustrates how crowding out in the choice behavior can arise. The choice probability is always decreasing in the price level when $a = 0$. Furthermore, at full price, $p = 100$, charitable donations increase demand. However, when $a > 0$, we observe several upward-sloping regions of demand where

[16]The smoothness of the model is established through the derivation of the gradients in Appendix A. Regularity is established for almost all solutions through Sard's Theorem and the fact that the model is continuously differentiable.

[17]We are grateful to Ron Borkovsky for his advice on the properties of the equilibrium correspondence of this model.

the choice probability is increasing in the price level. For instance, suppose we compare the campaigns $(a_1, p_1) = (15,70)$ and $(a_2, p_2) = (15,60)$ which moves us along a region of the demand correspondence that is uniquely defined at each price. The price reduction from campaign one to campaign two is counter-productive. Lowering the price raises the consumption utility since the movie is cheaper in the second campaign. But, the corresponding expected choice probability nevertheless falls from 0.027 to 0.0153. In this example, the decline in ego utility overwhelms the gain in consumption utility. The equilibrium self beliefs for the two campaigns are

$$\{E(\gamma|15,70,1) = 0.077,\ E(\gamma|15,70,0) = 0.0799,\ E(\alpha|15,70,1) = -0.0143,\ E(\alpha|15,70,0) = -0.0393\}$$

and

$$\{E(\gamma|15,60,1) = 4.6151,\ E(\gamma|15,60,0) = 0.0077, E(\alpha|15,60,1) = -1.6105,\ E(\alpha|15,60,0) = -0.0143\}$$

for campaigns one and two respectively. Given our estimated diagnostic weights $\lambda_\gamma = 9.5845$ and $\lambda_\alpha = 28.7377$, the ego returns decline from $\Delta(15,70) = 0.0268$ to $\Delta(15,60) = -1.7098$. For the average consumer who has expected price sensitivity of $E(\alpha) = -0.0386$, the $10RMB$ discount only raises her consumption utility by 0.386 and, hence, her total utility declines after the discount. Her consumption utility only rises by The source of this decline is the multi-dimensional heterogeneity in consumer tastes. The price decline draws in a more much more price-sensitive consumer to buy a ticket, which dampens the overall self-signal. Analogous forms of *muddled information* have been studied in the recent theoretical literature on multi-dimensional screening (e.g. Benabou and Tirole (2006); Frankel and Kartik (2014)).

Theoretically, one could find crowding out even if the self-signaling was only on γ. Although not reported herein, we do not find any evidence for crowding out in demand using our empirical estimates for the specification with self-signaling only on γ.

Figure 7 also reveals the potential for multiple equilibria. For some promotion campaigns (e.g. $a = 10$ and $a = 15$), we find that some price levels generate three different sets of equilibrium beliefs and, hence, three equilibrium share levels. This multiplicity confirms the importance of our MPEC estimator which was set up to select the equilibrium with the highest likelihood corresponding to a given set of structural parameters and a given observed promotional offer. For instance, when $p = 25.5$ RMB and $a = 16$, we find 3 equilibrium share levels: 0.039, 0.034 and 0.0178.

6.3.1 The non-fungibility of Promotion Money

The structural estimates also point towards an interesting non-fungibility of promotional funds. By revealed preference, we would typically expect a discount to be preferred to an equal-sized donation since the consumer could always donate the total amount of the discount to charity. However, once we account for ego utility, there may be promotional states in which an incremental donation might be preferred to an equal-sized incremental discount. We explore this issue by looking at the optimal promotional campaign design under different firm objectives: profit maximization and charitable funds maximization.

The multiplicity of equilibria complicates our counterfactual analysis of promotion campaigns. In-sample, our MPEC estimator selects the equilibrium with the highest likelihood. But, out-of-sample, we do not observe consumer choices. So we experiment with three different equilibrium selection rules[18]. Let $\mathscr{D}(a,p)$ denote the set of equilibrium posterior beliefs corresponding to a given price level p and donation level a. Our first selection rule is intended to capture the spirit of our MPEC estimator which selected the equilibrium in-sample with the highest-likelihood. Since we do not observe choices out-of-sample, we simulate them from our model. The selection rule is as follows:

$$\delta(a,p) = \underset{\delta\in\mathscr{D}(a,p)}{argmax}\left\{\hat{\ell}(\Gamma,\delta|a,p)\right\} \tag{9}$$

where

$$\begin{aligned}\hat{\ell}(\Gamma,\delta|a,p) &= \frac{1}{R}\sum_{r=1}^{R}\sum_{h=1}^{H}\left\{y^{h,r}log\left(Pr\left(y=1|a,p;\delta\right)\right)+\left(1-y^{h,r}\right)log\left(1-Pr\left(y=1|a,p;\delta\right)\right)\right\}\\ &\underset{R\to\infty}{\longrightarrow} Pr\left(y=1|a,p;\delta\right)log\left(Pr\left(y=1|a,p;\delta\right)\right)+\left(1-Pr\left(y=1|a,p;\delta\right)\right)log\left(1-Pr\left(y=1|a,p;\delta\right)\right)\end{aligned}$$

and the out-of-sample choices are drawn as follows: $y^{h,r}\sim Bernoulli(Pr\left(y=1|a,p;\delta\right)$.

Our second selection rule consists of choosing the most profitable equilibrium from the perspective of the seller:

$$\delta(a,p) = \underset{\delta\in\mathscr{D}(a,p)}{argmax}\left\{p\times Pr\left(y=1|a,p;\delta\right)\right\}. \tag{10}$$

Our third selection rule consists of choosing the equilibrium with the highest surplus from the perspective of the consumer:

$$\delta(a,p) = \underset{\delta\in\mathscr{D}(a,p)}{argmax}E\left\{max\left(U\right)\right\} \tag{11}$$

where U is defined as in 1.

On our grid of $27,217$ pairs of prices and donation levels, the profit and consumer surplus criteria select the same equilibrium in 98.4% of the cases. The consumer surplus and likelihood criteria select the same equilibrium in 100% of the cases. Hereafter, we use the likelihood selection criterion. For those points on the grid that coincide with our observed price and donations levels in-sample, the likelihood criterion selects the same equilibrium as the MPEC estimate in 100% of the cases.

[18]The nearest-neighbor approach in Aguirregabiria (2011) is not well-suited to our setting since the nature of our counterfactuals does not provide an obvious "factual" equilibrium to use as a base case.

Suppose the firm's objective consists of optimizing expected revenues:

$$(p^*, a^*) = \underset{p,a}{argmax} \{ p \times Pr(y = 1|a, p) \}. \tag{12}$$

If we restrict donations to be zero, $a = 0$, then revenues are maximized at $p^* = 20.5$ RMB. However, when we allow $a > 0$, then revenues are maximized at $p^* = 36.25$ RMB and $a^* = 1$. Interestingly, these results suggest that donations are not incompatible with revenue goals since a firm can increase its profits by using a small donation and raising its price. We can see this result in Figure 8, which plots the expected equilibrium revenue per customer for several alternative promotional campaigns. Recall from Figure 7 that for a low donation level like $a = 1$, the dampening of the self-signal does not start to crowd out demand until prices fall below 30 RMB, allowing the firm to benefit from a small donation.

Suppose instead the firm's objective consists of optimizing the total expected charitable funds raised through ticket sales:

$$(p^*, a^*) = \underset{p,a}{argmax} \{ a \times Pr(y = 1|a, p) \}. \tag{13}$$

Figure 9 plots the expected equilibrium charitable funds per customer under several campaign scenarios. Once again we see the effects of crowding out. At higher price levels, a price reduction can increase the expected charitable funds collected. However, large decreases in price can start to become counter-productive and crowd out demand. For large donation levels like $a = 15$, there is a discontinuous jump in the charitable revenues due to the backward-bending solution path we traced out in Figure 7. As a result, the charitable funds-maximizing prosocial campaign sets the price at $p^* = 20$ RMB and donations at $a^* = 16$. Therefore, the combination of a large donation and large discount is effective at raising funds for the charitable campaign.

These counterfactuals illustrate some of the economic implications of self-signaling for the design of a cause marketing campaign. For a firm that seeks to raise money for charity, large discounts and large donations can be very effective. However, for a firm trying to generate revenues, a small donation can improve revenues when bundled with higher prices.

7 Conclusions

In a large-scale, cause marketing field experiment, we find that the combination of promotional discounts and charitable donations can reduce demand for the underlying product. Our evidence supports a theory of self-signaling whereby consumers are partially motivated to buy the product to derive a warm-glow feeling from supporting the cause. The crowding out of demand arises when price discounts dampen the self-signal of altruistic motivation. The results provide field evidence of ego utility as a determinant of consumer choices.

We quantify the self-signaling both with an attitudinal survey and with a structural model fit to purchase data. At face value, our structural estimates imply that the average consumer derives utility from the self-perception of valuing charity more than from the actual act of charitable giving. Our findings also contribute to the broader literature on social preferences and the important role of beliefs in understanding consumer preferences in prosocial contexts. In particular, under self-signaling, discounts and donations are not inherently complementary and, over some regions, discounts can offset the demand-shifting effects of a donation. Furthermore, counterfactual experiments reveal an incompatibility in the use of discounts and donations when a firm pursues revenue goals as opposed to charitable goals.

Our results pertain to demand for movie tickets, which may be perceived as hedonic goods. It is unclear whether our evidence for self-signaling would generalize to other contexts with more utilitarian goods or neutral goods (Savary, Goldsmith, and Dhar (2014)).

Our study is limited to the immediate effect of self-signaling. An interesting direction for future research would be to explore whether consumers who experience a higher warm-glow feeling today are more likely to engage in a future prosocial behavior. This type of state-dependence might arise if consumers accumulate a prosocial self-image capital stock (Benabou and Tirole (2011)) or if they literally impute their own preferences from past actions (Ariely and Norton (2007)). Gneezy, Imas, Brown, Nelson, and Norton (2012) provide lab evidence that increasing the costs of the self-signal not only increases its diagnostic value, it also increases the likelihood of repeated prosocial behavior. It is possible that a high warm-glow feeling in a cause marketing campaign similar to the one we study increases subsequent prosocial behavior by consumers.

It would also be interesting to study whether consumers value the opportunity to self-signal or, ultimately, prefer to avoid being placed in self-signaling situations. Our respondents had no way to avoid being assigned to the campaign. However, if given the chance, it would be interesting to see whether consumers would opt-out of receiving offers like the ones we study to avoid the pressure of being confronted with a self-signaling opportunity (DellaVigna, List, and Malmendier (2012)).

Finally, our research does not address whether consumers learn about the firm's social preferences based on the cause marketing campaign. Using our parameter estimates, a firm would use a small donation to generate revenues and a large donation to stimulate charitable funds. It would be interesting to analyze the equilibrium implications of consumers having preferences for the firm's social preferences. This scenario would entail a social-signaling game in which the firm uses its campaign to signal its altruism to consumers.

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Variable	Donation (RMB)						
		0	**3**	**6**	**15**	**30**	**36**
discount (RMB)	**0**	500	500	500	500	500	500
	3	500	500	500	500	500	
	6	500	500	500	500		
	15	500	500	500			
	30	500	500				
	36	500					

Table 1: Experimental Design and Sample Size for Study 1

Note. Each cell contains the total number of subjects assigned to the corresponding experimental condition.

Variable	Donation (RMB)				
		0	**5**	**10**	**15**
discount (RMB)	**0**	700	700	700	700
	20	700	1,000	1,000	1,000
	35	700	1,000	3,000	3,000
	50	700	1,000	3,000	3,000
	60	700	1,000	3,000	3,000
	75	700	-	-	-

Table 2: Experimental Design and Sample Size for Study 2

Note. Each cell contains the total number of subjects assigned to the corresponding experimental condition.

Variable	Obs	Mean	Std.	Min	Max
purchase	30,300	0.0229	0.150	0	1
ARPU	30,300	74.109	51.192	8.07	688.98
MOU	30,300	633.498	611.451	1	5647
SMS	30,300	365.028	243.656	0	3099
GPRS	30,300	63885.97	202239.2	34	1.22E+07

Table 3: Summary Statistics

Note. Each cell contains the total number of subjects assigned to the corresponding experimental condition.

discount	donation	# respondents
20	5	25
20	10	29
20	15	29
35	5	26
35	10	25
35	15	27
50	5	23
50	10	27
50	15	29
60	5	35
60	10	27
60	15	27

Table 4: Survey Response Rate

Variable	Donation (RMB)						
		0	**3**	**6**	**15**	**30**	**36**
discount (RMB)	**0**	0.000	0.004	0.006	0.010	0.040**	0.046**
	3	0.006	0.016*	0.018*	0.020**	0.044**	-
	6	0.008	0.020**	0.022**	0.024**	-	-
	15	0.034**	0.032**	0.028**	-	-	-
	30	0.062**	0.040**	-	-	-	-
	36	0.066**	-	-	-	-	-

Table 5: Experimental Results for Study 1

Note. Each cell contains the purchase frequency across subjects in the specific marketing condition.

** Significant at the 1 percent level

* Significant at the 5 percent level

Variable	Donation (RMB)				
		0	**5**	**10**	**15**
Discount (RMB)	**0**	0.0000	0.0043	0.0057	0.0114*
	20	0.0071	0.0170**	0.0200**	0.0240**
	35	0.0329**	0.0300**	0.0270**	0.0230**
	50	0.0557**	0.0420**	0.0180**	0.0160**
	60	0.0600**	0.0480**	0.0170**	0.0140**
	75	0.0629**	-	-	-

Table 6: Experimental Results for Study 2

Note. Each cell contains the purchase frequency across subjects in the specific marketing condition.

** Significant at the 1 percent level

* Significant at the 5 percent level

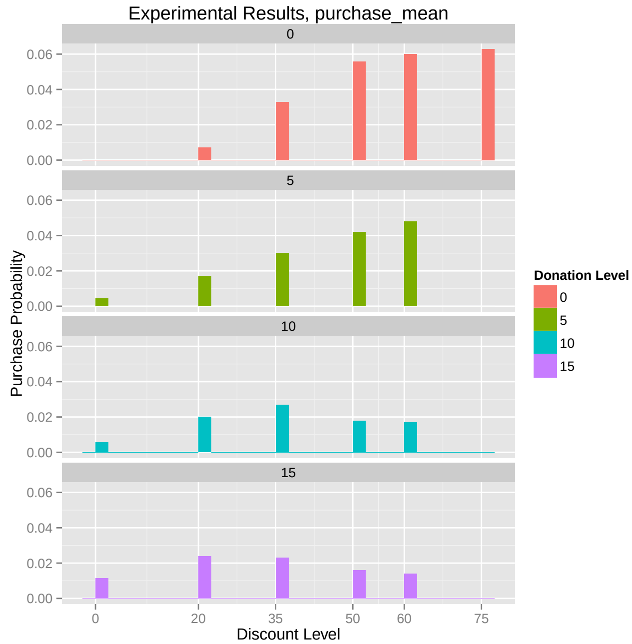

Figure 1: Purchase rate by promotional condition

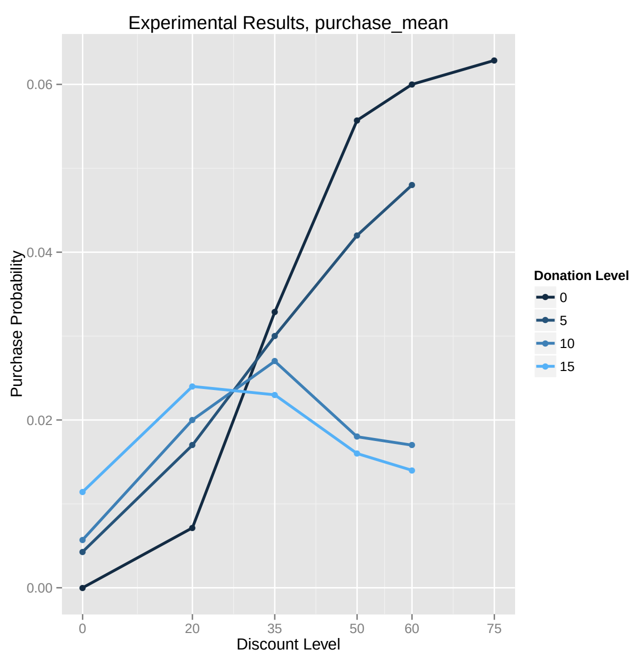

Figure 2: Purchase rate by promotional condition

问卷设计(Survey Design) for NOT purchased customers

1、您好，这里是****，可以耽误你 5 分钟的时间，做个满意度调查吗？（如果客户同意，则继续）谢谢！

Dear customer, on behalf of (wireless provider), would you please participate in a short (5 minutes) customer satisfaction survey? (if yes, please continue)

2、您觉得****的手机支付业务是否方便？

Do you believe (wireless provider)'s mobile payment business is easy to use?

3、

****前期推出了"看电影做公益"活动。昨天有用户通过****购买了"X 战警：逆转未来"的电影票通兑券，享受 yyy 折优惠，还通过****为贫困孤独老人捐助 zzz 元。您认为，这些用户参与本次活动、购买电影票的原因最可能是以下哪一种. 我们想了解一下这些用户对本次购买的原因，以便改进业务，服务客户：

As you know, ****(wireless provider) launched a Mobile Movie Ticket business. Through this app, yesterday consumers purchased tickets for the movie *X-Men: Days of Future Past* using a special offer that donated YYY ¥ per ticket to a charity for poor elderly and also discounted the regular ticket price by ZZZ." To improve our business and customer service, please indicate the extent to which you agree with the following statement about why those consumers bought tickets:

the same as above except the different discount zzz# and donation yyy# across the treatments.

(1)是因为想看电影，有没有折扣和捐赠，都会购买。

They wanted to watch the movie and would have seen it regardless of the special offer.

(2)是因为折扣很大很划算。

The discount was big enough to make it worthwhile for them to buy a movie ticket.

(3)是因为看重和支持本次捐助活动。

They valued the charity and wanted to support it.

(4)是因为向贫困老人捐钱后，他们对自己的感觉较好。

They wanted to feel good about themselves by donating to the charity.

4、您认为，这些用户以后是否会继续参与"看电影做公益"活动，捐更多的钱？

Do you think those consumers will continue donating money to this charity in the future?

5、您觉得，这些用户是否相信本次捐赠活动是真实可信的呢？

Do you think this SMS donation deal seems too good to be true for those consumers?

6、您觉得，这些用户是否认为他们就有责任去关心贫困孤独老人？

How strongly do you feel those consumers should care about the poor elderly in need?

7、您觉得，这些用户是否觉得自己是个有爱心的人？

In general, do you feel those consumers consider themselves caring people?

8、您觉得，这些用户本次购买是否是冲动购物？

Do you think this purchase is an impulse buy for those consumers?

Figure 3: Survey Questions for non-purchasers

问卷设计(Survey Design) for purchased customers

1、您好，这里是****，可以耽误你 5 分钟的时间，做个满意度调查吗？（如果客户同意，则继续）谢谢！

Dear customer, this is ****(wireless provider), would you please take a short time 5 min and participate in our customer satisfaction survey?(if yes, continue)

2、您觉得****的手机支付业务是否方便？（掩饰性问题）

Do you think that ****(wireless provider)'s mobile payment business is easy to use? (to cover the real purpose of this survey)

3、

(1) ****前期推出了"看电影做公益"活动。昨天您通过****购买了"X 战警：逆转未来"的电影票通兑券，享受 8 折优惠，还通过****为贫困孤独老人捐助 5 元。我们想了解一下对您本次购买的原因，以便改进业务，服务客户：

As you know, ****(wireless provider) launched Mobile Movie Ticket Buying business. Through this app, yesterday you (the consumer) just purchased a ticket for the movie *X-Men: Days of Future Past* using a special offer that donated YYY ¥ per ticket to help poor elderly charity and also discounted the regular ticket price by ZZZ." Please indicate to what extent you agree with the following statement regarding why consumers made the purchase in order to improve our business and customer service:

the same as above except the different discount zzz# and donation yyy# across the treatments.

(1) 您本次购买，是因为想看电影，有没有折扣和捐赠，都会购买。

The consumer wanted to watch the movie and would have seen it regardless of the special offer.

(2)您本次购买，是因为折扣很大很划算。

The discount was big enough to make it worthwhile for the consumer to buy a ticket to watch the movie.

(3)您本次购买，是因为您看重和支持本次捐助活动。

The consumer values the charity and wanted to support it.

1

(4)您本次购买，是因为向贫困老人捐钱后，您对自己的感觉较好。

The consumer wanted to feel good about herself by donating to the charity.

4、以后，您是否继续参与"看电影做公益"活动，捐更多的钱？

Do you think you will continue donating money to this charity in the future?

5、您是否认为本次捐赠活动是真实可信的呢？

This SMS deal seems too good to be true.

6、您是否认同我们应该关心贫困孤独老人？

How strongly do you feel we ourselves should care about the poor elderly in need?（to rule out charity responsibility）

7、您是否觉得您是个有爱心的人？

In general, I consider myself a caring person.

8、你本次购买是否因为冲动购物？

Do you think this purchase was an impulse buy?

2

Figure 4: Survey Questions for purchasers

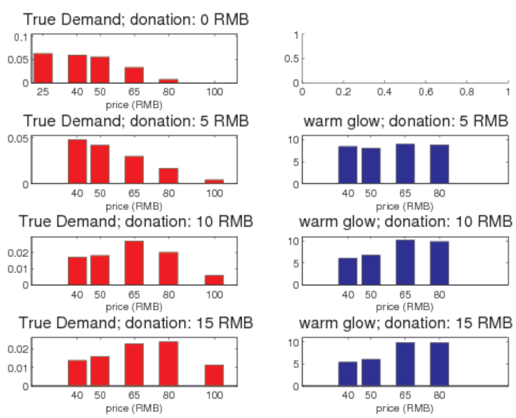

Figure 5: Survey: Warm Glow Feeling

Notes: The left panel reports the average purchase frequencies for each of the 21 campaigns. The right panel reports the average rating of the survey question "I wanted to feel good about myself" as a motivation for buying a ticket corresponding to those campaign cells for which we conducted the survey.

	Probit	*R.C. Probit*		*Self-Signaling on γ*		*Self-Signaling on γ and α*		*Self-Signaling on γ and V*	
		comp 1	comp 2	comp 1	comp 2	comp 1	comp 2	comp 1	comp 2
Donation, γ	-0.022	-0.0827	0.2621	-0.2887	0.0411	0.0077	4.6818	-0.2887	0.0411
	(0.0031)	(0.0208)	(0.147)	(0.1324)	(0.0928)	(0.0051)	(0.7609)	(0.116)	(0.1111)
Price, α	-0.0063	-0.0137	-0.114	-0.0163	-0.0945	-0.0143	-1.6336	-0.0163	-0.0945
	(0.001)	(0.004)	(0.0432)	(0.0022)	(0.0204)	(0.0011)	(0.2969)	(0.0018)	(0.0284)
Intercept , V	-1.4373	-1.2218	8.1799	-1.1449	6.6262	-1.061	35.1249	-1.1449	6.6262
	(0.0581)	(0.1644)	(3.1617)	(0.1152)	(1.3899)	(0.057)	(7.2856)	(0.0847)	(2.035)
mixing prob, ω	-	0.981	-	0.981	-	0.985	-	0.981	-
	-	(0.0017)	-	(0.0009)	-	(0.0016)	-	(0.0011)	-
λ_γ	-	-	-	7.061	-	9.5845	-	0.0739	-
	-	-	-	(2.8705)	-	(0.2504)	-	(0.3702)	-
λ_α	-	-	-	-	-	28.7377	-	-	-
	-	-	-	-	-	(0.0612)	-	-	-
λ_V	-	-	-	-	-	-	-	0.2965	-
	-	-	-	-	-	-	-	(0.2292)	-
log-likelihood, ℓ	-3254.09	-3215.08		-3208.02		-3203.45		-3208.02	
AIC	6514.17	6444.16		6432.04		6424.89		6434.04	

Table 7: Structural Estimates and Model Fits (finite mixture model of heterogeneity)

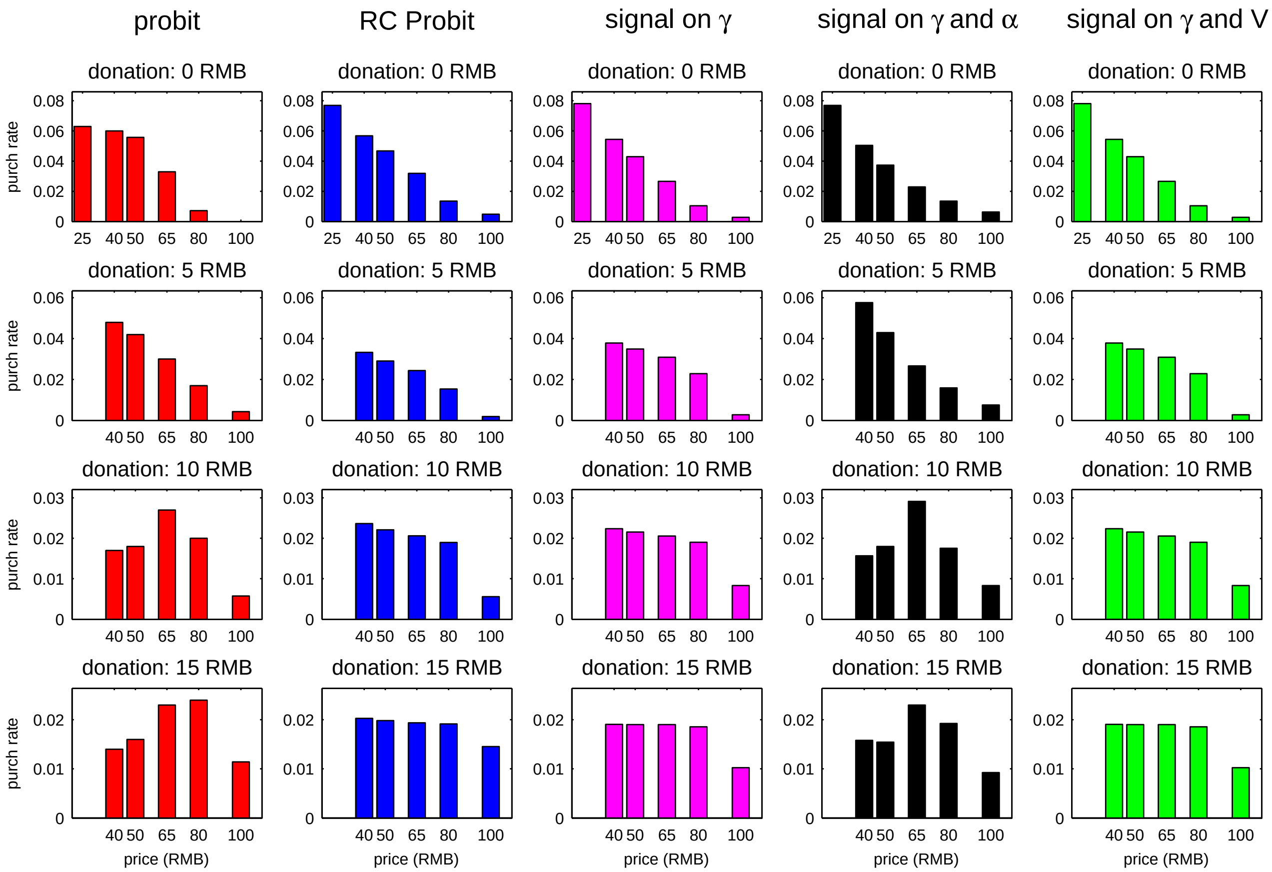

Figure 6: In-Sample Fit of the Structural Models

Notes: First column has true shares (red). Columns two through six have predicted shares from R.C. Probit (blue), self-signaling on γ only (magenta), self-signaling on γ and α (black), self-signaling on γ and V (green).

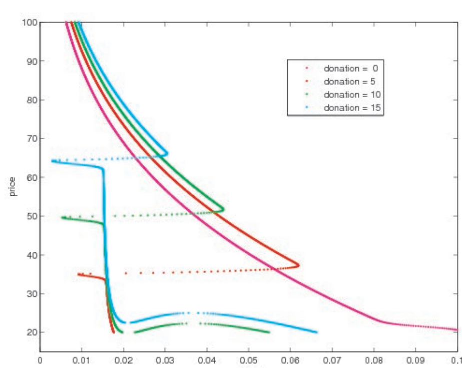

Figure 7: Equilibrium choices under different promotional campaigns

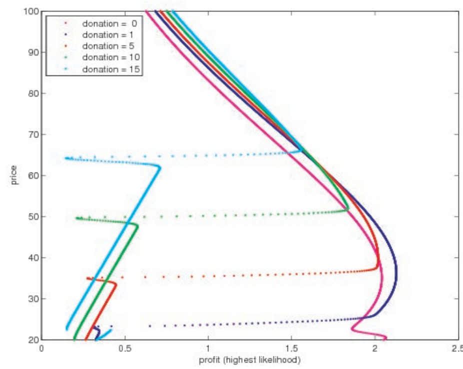

Figure 8: Equilibrium revenues under different promotional campaigns

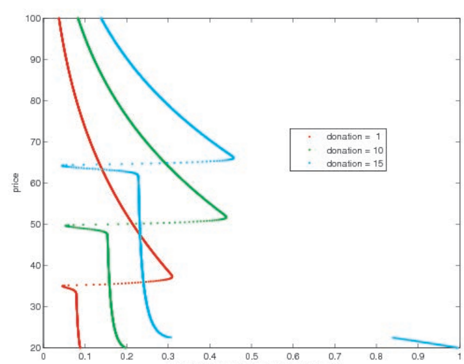

Figure 9: Equilibrium charitable funds under different promotional campaigns

A Appendix: Gradients of the MPEC Estimator

Recall that our MPEC estimator maximizes the log-likelihood function

$$\ell(\Gamma,\delta)=\sum_h \left(y^h ln\left(Pr\left(y^h=1|p_t,a_t;\Gamma,\delta_t\right)\right)+\left(1-y^h\right)ln\left(1-Pr\left(y^h=1|a_t,p_t;\Gamma,\delta_t\right)\right)\right)$$

subject to the constraints

$$G(\delta_{\mathbf{t}})\equiv\begin{bmatrix}\delta_{\gamma 1t}-\frac{\sum_k \gamma^k \Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k}{\sum_k \Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k}\\ \\ \delta_{\gamma 2t}-\frac{\sum_k \gamma^k\left[1-\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\right]\omega^k}{\sum_k\left[1-\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\right]\omega^k}\\ \\ \delta_{\alpha 1t}-\frac{\sum_k \alpha^k \Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k}{\sum_k \Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k}\\ \\ \delta_{\alpha 2t}-\frac{\sum_k \alpha^k\left[1-\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\right]\omega^k}{\sum_k\left[1-\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\right]\omega^k}\end{bmatrix}=0$$

where

$$Pr\left(y^h=1|p_t,a_t;\Gamma,\delta_t\right)=\sum_k \Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k$$

and

$$u_t\left(\Gamma^k,\delta_t\right)=V^k+\gamma^k a_t+\alpha^k p_t+\Delta(a_t,p_t,\Lambda)$$

and

$$\Delta(a_t,p_t,\Lambda) \quad = \quad \lambda_\gamma\left(\delta_{\gamma 1t}-\delta_{\gamma 2t}\right)+\lambda_\alpha\left(\delta_{\alpha 1t}-\delta_{\alpha 2t}\right).$$

Define x_{jt} where $j=1,...,J$. Let $j\in\{\alpha,\gamma,V\}$. The gradients of the objective function are

$$\begin{aligned}
\frac{\partial\ell(\Gamma,\delta)}{\partial\theta_j^i} &= \sum_h y^h x_{jt}\frac{\phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^i}{\sum_s \Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k}-\sum_h\left(1-y^h\right)x_{jt}\frac{\phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^i}{\sum_k\left[1-\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]}\\
\frac{\partial\ell(\Gamma,\delta)}{\partial\omega^i} &= \sum_h y^h\frac{\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)-\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)}{\sum_s \Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k}-\sum_h\left(1-y^h\right)\frac{\left(1-\Phi\left(u_t\left(\Gamma^i\right)\right)\right)-\left(1-\Phi\left(u_t\left(\Gamma^K\right)\right)\right)}{\sum_k\left[1-\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]}\\
\frac{\partial\ell(\Gamma,\delta)}{\partial\lambda_j} &= \sum_h y^h\left(\delta_{j1t}-\delta_{j2t}\right)\frac{\sum_s\phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k}{\sum_s \Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k}-\sum_h\left(1-y^h\right)\left(\delta_{j1t}-\delta_{j2t}\right)\frac{\sum_s\phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k}{\sum_k\left[1-\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]}\\
\frac{\partial\ell(\Gamma,\delta)}{\partial\delta_{jkt}} &= \sum_{h\tau|\tau=t} y^{h\tau}\lambda_\gamma(-1)^{(2-k)}\frac{\sum_s\phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k}{\sum_s \Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k}-\sum_{h\tau|\tau=t}\left(1-y^{h\tau}\right)\lambda_\gamma(-1)^{(2-k)}\frac{\sum_s\phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k}{\sum_s \Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k}
\end{aligned}$$

The gradients for the constraints are

$$\frac{\partial Gn_1(\boldsymbol{\delta}_\mathbf{t})}{\partial\theta^i_j} = -\frac{\Phi\left(u_t\left(\Gamma^i,\delta_t\right)\right)\omega^i}{\left[\sum_k\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]^2}\mathbb{I}_{\{j=\gamma\}} - x_{jt}\,\frac{\theta^i_n\phi\left(u_t\left(\Gamma^i\right)\right)\omega^i\left[\sum_k\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]-\left[\sum_k\theta^k_n\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]\phi\left(u_t\left(\Gamma^i,\delta_t\right)\right)\omega^i}{\left[\sum_k\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]^2}$$

$$\frac{\partial Gn_2(\boldsymbol{\delta}_\mathbf{t})}{\partial\theta^i_j} = -\frac{\left(1-\Phi\left(u_t\left(\Gamma^i,\delta_t\right)\right)\right)\omega^i}{\left[\sum_k\left(1-\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\right)\omega^k\right]^2}\mathbb{I}_{\{j=\gamma\}} + x_{jt}\,\frac{\theta^i_n\phi\left(u_t\left(\Gamma^i,\delta_t\right)\right)\omega^i\left[\sum_k\Phi\left(-u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]-\left[\sum_k\theta^k_n\Phi\left(-u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]\phi\left(u_t\left(\Gamma^i,\delta_t\right)\right)\omega^i}{\left[\sum_k\Phi\left(-u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]^2}$$

$$\frac{\partial G_{n1}(\boldsymbol{\delta}_\mathbf{t})}{\partial\omega^i} = -\frac{\left[\theta^i_n\Phi\left(u_t\left(\Gamma^i,\delta_t\right)\right)-\gamma^K\Phi\left(u_t\left(\Gamma^K,\delta_t\right)\right)\right]\left[\sum_k\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]-\left[\sum_k\theta^k_n\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]\left[\Phi\left(u_t\left(\Gamma^i,\delta_t\right)\right)-\Phi\left(u_t\left(\Gamma^K,\delta_t\right)\right)\right]}{\left[\sum_k\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]^2}$$

$$\frac{\partial G_{n2}(\boldsymbol{\delta}_\mathbf{t})}{\partial\omega^i} = -\frac{\left[\theta^i_n\Phi\left(-u_t\left(\Gamma^i,\delta_t\right)\right)-\gamma^K\Phi\left(-u_t\left(\Gamma^K,\delta_t\right)\right)\right]\left[\sum_k\Phi\left(-u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]-\left[\sum_k\theta^k_n\Phi\left(-u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]\left[\Phi\left(-u_t\left(\Gamma^i,\delta_t\right)\right)-\Phi\left(-u_t\left(\Gamma^K,\delta_t\right)\right)\right]}{\left[\sum_k\Phi\left(-u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]^2}$$

$$\frac{\partial G_{n1}(\boldsymbol{\delta}_\mathbf{t})}{\partial\lambda_j} = -\left(\delta_{j1t}-\delta_{j2t}\right)\,\frac{\left[\sum\theta^k_n\phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]\left[\sum_k\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]-\left[\sum_k\theta^k_n\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]\left[\sum_k\phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]}{\left[\sum_k\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]^2}$$

$$\frac{\partial G_{n2}(\boldsymbol{\delta}_\mathbf{t})}{\partial\lambda_j} = \left(\delta_{j1t}-\delta_{j2t}\right)\,\frac{\left[\sum_k\theta^k_n\phi\left(u_t\left(\Gamma^{ik},\delta_t\right)\right)\omega^k\right]\left[\sum_k\Phi\left(-u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]-\left[\sum_k\theta^k_n\Phi\left(-u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]\left[\sum_k\phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]}{\left[\sum_k\Phi\left(-u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]^2}$$

$$\frac{\partial G_{n1}(\boldsymbol{\delta}_\mathbf{t})}{\partial\delta_{n1t}} = 1-\lambda_n\,\frac{\left[\sum\theta^k_n\phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]\left[\sum_k\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]-\left[\sum_k\theta^k_n\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]\left[\sum_k\phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]}{\left[\sum_k\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]^2}$$

$$\frac{\partial G_{n2}(\boldsymbol{\delta}_\mathbf{t})}{\partial\delta_{n2t}} = 1-\lambda_n\,\frac{\left[\sum_k\theta^k_n\phi\left(u_t\left(\Gamma^{ik},\delta_t\right)\right)\omega^k\right]\left[\sum_k\Phi\left(-u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]-\left[\sum_k\theta^k_n\Phi\left(-u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]\left[\sum_k\phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]}{\left[\sum_k\Phi\left(-u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]^2}\qquad, \ \text{n,j=1,...,J,i=1,...,K}$$

$$\frac{\partial Gn_1(\boldsymbol{\delta}_\mathbf{t})}{\partial\delta_{n2t}} = \lambda_n\,\frac{\left[\sum\theta^k_n\phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]\left[\sum_k\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]-\left[\sum_k\theta^k_n\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]\left[\sum_k\phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]}{\left[\sum_k\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]^2}$$

$$\frac{\partial Gn_2(\boldsymbol{\delta}_\mathbf{t})}{\partial\delta_{n1t}} = \lambda_n\,\frac{\left[\sum_k\theta^k_n\phi\left(u_t\left(\Gamma^{ik},\delta_t\right)\right)\omega^k\right]\left[\sum_k\Phi\left(-u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]-\left[\sum_k\theta^k_n\Phi\left(-u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]\left[\sum_k\phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]}{\left[\sum_k\Phi\left(-u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]^2}$$

$$\frac{\partial G_{n1}(\boldsymbol{\delta}_\mathbf{t})}{\partial\delta_{j1t}} = -\lambda_j\,\frac{\left[\sum\theta^k_n\phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]\left[\sum_k\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]-\left[\sum_k\theta^k_n\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]\left[\sum_k\phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]}{\left[\sum_k\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]^2}$$

$$\frac{\partial G_{n2}(\boldsymbol{\delta}_\mathbf{t})}{\partial\delta_{j2t}} = -\lambda_j\,\frac{\left[\sum_k\theta^k_n\phi\left(u_t\left(\Gamma^{ik},\delta_t\right)\right)\omega^k\right]\left[\sum_k\Phi\left(-u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]-\left[\sum_k\theta^k_n\Phi\left(-u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]\left[\sum_k\phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]}{\left[\sum_k\Phi\left(-u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]^2}$$

$$\frac{\partial Gn_1(\boldsymbol{\delta}_\mathbf{t})}{\partial\delta_{j2t}} = \lambda_j\,\frac{\left[\sum\theta^k_n\phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]\left[\sum_k\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]-\left[\sum_k\theta^k_n\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]\left[\sum_k\phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]}{\left[\sum_k\Phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]^2}$$

$$\frac{\partial Gn_2(\boldsymbol{\delta}_\mathbf{t})}{\partial\delta_{j1t}} = \lambda_j\,\frac{\left[\sum_k\theta^k_n\phi\left(u_t\left(\Gamma^{ik},\delta_t\right)\right)\omega^k\right]\left[\sum_k\Phi\left(-u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]-\left[\sum_k\theta^k_n\Phi\left(-u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]\left[\sum_k\phi\left(u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]}{\left[\sum_k\Phi\left(-u_t\left(\Gamma^k,\delta_t\right)\right)\omega^k\right]^2}$$

B Survey Results

Below we include some additional survey results that support our baseline theory of self-signaling.

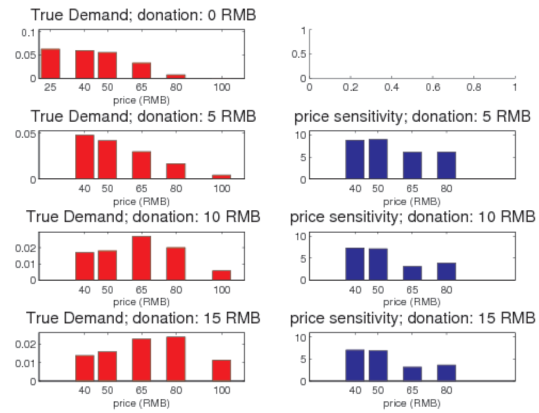

Figure 10: Survey: Price Sensitivity

Notes: The left panel reports the average purchase frequencies for each of the 21 campaigns. The right panel reports the average rating of the survey question "the discount was big enough to make it worthwhile for your to buy a movie ticket" as a motivation for buying a ticket corresponding to those campaign cells for which we conducted the survey.

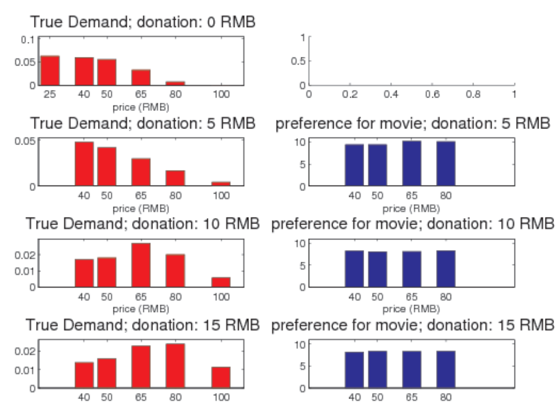

Figure 11: Survey: want to see the movie

Notes: The left panel reports the average purchase frequencies for each of the 21 campaigns. The right panel reports the average rating of the survey question "you wanted to watch the movie" as a motivation for buying a ticket corresponding to those campaign cells for which we conducted the survey.

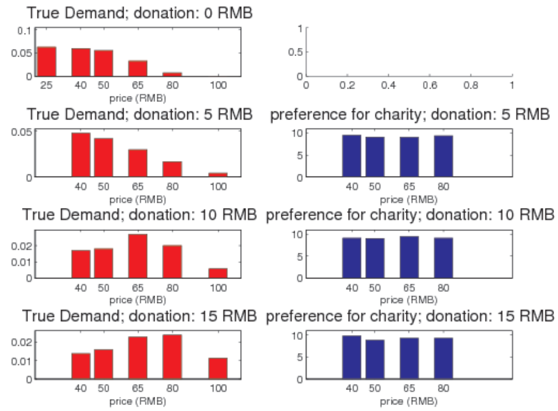

Figure 12: Survey: Value the Charity itself

Notes: The left panel reports the average purchase frequencies for each of the 21 campaigns. The right panel reports the average rating of the survey question "You valued the charity and wanted to support it" as a motivation for buying a ticket corresponding to those campaign cells for which we conducted the survey.

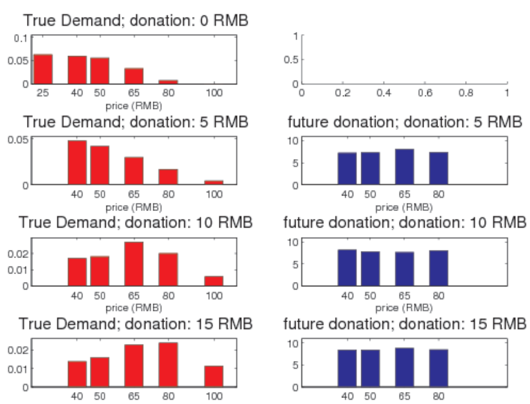

Figure 13: Survey: Intend to donate to charity in future

Notes: The left panel reports the average purchase frequencies for each of the 21 campaigns. The right panel reports the average rating of the survey question "Will you continue donating money to this charity in the future?" corresponding to those campaign cells for which we conducted the survey.