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# Self-Signaling and Prosocial Behavior: A Cause Marketing Experiment

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**Abstract.** We test an information theory of prosocial behavior whereby ego utility and self-signaling crowd out the effect of consumption utility on choice. The data come from two field experiments involving purchases of a consumer good bundled with a charitable donation. Across experimental cells, we randomize the price level and the donation level. A model-free analysis of the data reveals nonmonotonic regions of demand when the good is bundled with relatively large charitable donations. Subjects also self-report lower ratings of “feeling good about themselves” when offered bundles with large donations and price discounts. The evidence suggests that price discounts crowd out consumer self-inference of altruism. Alternative motivation-crowding theories are rejected due to their inability to explain the nonmonotonic data moments. The standard use of interaction effects and other falsification checks to explore the underlying choice mechanism in an experimental setting is complicated in our self-signaling context. Instead, a novel feature of our analysis consists of using the experimental data to estimate the structural form of a model of consumer demand with self-signaling. We specify a model in which consumers obtain both consumption and ego utility from their choices. Ego utility derives from a consumer’s posterior self-beliefs after making her choice. An estimator is proposed that handles the potential multiplicity of equilibria that can arise in the self-signaling model. The model estimates allow us to quantify the economic role of ego utility and to explore the underlying signaling mechanism. Nested tests reject the hypothesis of no self-signaling. Alternative model specifications that potentially allow for nonmonotonic demand without the self-signaling structure exhibit an inferior fit to the data. The model estimates imply that consumer response to the donations are mainly driven by ego utility and not by consumption utility (i.e., not by altruistic motives). The findings from the combination of a field experiment and a structural model contribute to a growing literature on self-signaling and consumer behavior by quantifying the magnitude of self-signaling on preferences and choices. The results also have implications for the design of a cause marketing campaign and the potential negative synergies between price and nonprice promotions.

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## 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 (1970). Titmuss (1970) conjectured that paying blood donors could backfire by crowding out a

prospective donor’s altruistic incentive to donate blood through commercialization. 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 counterintuitively reduce the supply of prosocial behavior (e.g., see the surveys in Frey and Jegen 2001, Bowles and Polania-Reyes 2012). A parallel literature in psychology has studied situations

in which extrinsic (economic) incentives can crowd out an intrinsically 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.<sup>1</sup>

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 to have ulterior motives.

This paper explores a related reputational motivation driven by self-image, as opposed to social image. Using the analogy of interpersonal agency models,<sup>2</sup> Bodner and Prelec (2002) and Prelec and Prelec (2010) study intrapersonal agency<sup>3</sup> in a model of simultaneous "dual selves": a decider who chooses an action and a judge who interprets the action.<sup>4</sup> The decider receives consumption utility from the action and the judge receives self-diagnostic "ego utility" from the interpretation of the action.<sup>5</sup> The model 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 and thus manipulate her ego utility. 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.<sup>6</sup> Like Gneezy et al. (2012a), 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 theatre.

Each subject was randomly assigned to one of several promotional campaigns for a movie ticket and was then contacted via short message service (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 predetermined 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 24 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 both 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 nonmonotonicities that are consistent with self-signaling theory. For relatively small donations, discounts increase demand. However, for even moderate-sized donations, we see a nonmonotonic 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 (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. While we can rule out two alternative motivation-crowding explanations, a limitation of our experiments is that we cannot use them to falsify our main self-signaling theory.

A novel aspect of our analysis relative to past research using experiments is that we use the experimentally generated data to estimate the parameters of

a fully specified structural model of demand (Card et al. 2011). This structural approach overcomes one of the key weaknesses with field experiments, which is the difficulty in studying the underlying behavioral mechanism. Traditional solutions consist of using interaction effects, supplementary laboratory studies, or survey data. The structural model enables us to conduct a structural test for self-signaling behavior and its ability to explain the observed nonmonotonicity in consumer responses to price discounts in our experiment. We show that our self-signaling specification has superior statistical fit and is able to fit the non-monotonic choice moments, in contrast with several alternative specifications. Similar to DellaVigna et al. (2012), we also use the structural estimates of consumer preferences to describe and quantify the underlying consumer preferences. We find that the average consumption utility from donations is small and negative. By 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 that of 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 the Benabou and Tirole (2006) model.

The structural component of the analysis of experimental data introduces several methodological challenges. The primitives to be estimated are parameters characterizing consumers' preferences. The identification of these parameters and our ability to characterize self-signaling behavior requires several underlying assumptions, only some of which are rationalizable through the economic theory of the consumer. An additional identification challenge arises from the potential multiplicity of equilibria that can emerge from the demand model. We devise a constrained optimization estimator that produces consistent estimates of the demand parameters that are robust to this multiplicity. We also explore different equilibrium selection mechanisms in our counterfactual analysis of a firm's optimal price and donation decisions.

Our work is closely related to the empirical literature studying self-deceptive behavior (Quattrone and Tversky 1984, Shafir and Tversky 1992, Mijovic-Prelec et al. 1994, Dhar and Wertenbroch 2012, Gneezy et al. 2012a, Savary et al. 2015). 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 et al. (2004) find that social isolation moderates subjects' stated preferences over donations to a nonprofit enterprise. Field experiments by Ariely et al. (2009) and Ashraf et al. (2014) 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 et al. (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 this 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. Our empirical results are summarized in Section 5. The estimator for the structural form of the model is discussed in Section 6. 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 predetermined portion of the ticket price to a predetermined 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.

Over the 30-year period ending in 2012, corporate donations to charities grew at a rate exceeding inflation by 115%, reaching \$18 billion in 2012 (Stern 2013). In recent years, cause marketing has become an increasingly popular marketing tactic for generating corporate donations, with total U.S. spending increasing each year since at least 2002 and predicted to reach \$2.06 billion by the end of 2017 (IEG 2016). 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 et al. 2012). Industry experts share this view, advising firms that more sponsorship raises consumer support. Cause marketing consultant Paul Jones explains that “[c]ause marketing works because people have an affinity for the cause or the cause’s mission and want to support it” (Bennett 2007). 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 a 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 nonmonotonicity in demand. In particular, for large discount levels, we find that larger donations may counterintuitively reduce ticket demand. Based on these findings, a firm designing a cause marketing campaign should limit its use of noncomplementary 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 counterproductive when combined with donations.

### 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 predetermined 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.<sup>7</sup> 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.<sup>8</sup> 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 nonpurchase.

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

$$U = \begin{cases} (V + \gamma a + \alpha p + \epsilon_1) + R(a, p, \Lambda, 1), & y = 1, \\ R(a, p, \Lambda, 0) + \epsilon_0, & y = 0, \end{cases} \quad (1)$$

where  $\Theta = (V, \alpha, \gamma)$  are consumption utility parameters,  $\Lambda = (\lambda_\gamma, \lambda_\alpha)$  are ego utility parameters, and  $\epsilon_1$  and  $\epsilon_0$  are random utility shocks from buying and not buying a ticket, respectively. The first utility component,  $(V + \gamma a + \alpha p)$ , denotes the net consumption utility of the offer. The second term

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

denotes the consumer’s ego utility (or diagnostic utility). One could think of this term as the increase in self-esteem from the donation. The coefficients  $\lambda_\gamma$  and  $\lambda_\alpha$  are the diagnostic utility weights on the consumer’s posterior beliefs about  $\gamma$  and  $\alpha$ , 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,  $y$ .<sup>9</sup>

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. This “dual-process” approach to decision making builds on a large and well-established literature that models an individual with conflicting objectives (see Brocas and Carrillo 2014 for a comprehensive literature survey). A seemingly paradoxical aspect of the theory is that the individual simultaneously possesses two conflicting beliefs. In our setting, the decision-making module of the brain knows consumption preferences, but the judgment module of the brain is uncertain about consumption preferences. The neuroscience literature has provided compelling empirical evidence for single individual responses conveying such conflicting beliefs (e.g., Mijovic-Prelec et al. 1994). An alternative, dynamic intrapersonal agency formulation sets up the

decision problem in two stages. First, the decision-making “self” chooses. In a second stage, the judge “self” recalls the behavior but has “imperfect recall” regarding the underlying motivation for the behavior (e.g., Benabou and Tirole 2004, Bernheim and Thomsen 2005). In this case, the decision-making “self” can strategically adjust the “signal” value contained in her current behavior. Our empirical analysis does not attempt to distinguish between the former modular view and the latter dynamic intrapersonal view of self-deception.

The consumer purchases the ticket if

$$V + \gamma a + \alpha p + \Delta(a, p, \Lambda) + \epsilon > 0, \quad (3)$$

where  $\epsilon = \epsilon_1 - \epsilon_0$ . 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  $F(\Theta, \epsilon)$ . We follow convention in the demand estimation literature and let  $\epsilon \sim N(0, 1)$ , giving the classic random coefficients probit model of choice. The unconditional (expected) probability that the consumer purchases movie ticket offer  $(a, p)$  is

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

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

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

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 6.4, 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 6.4, 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.<sup>10</sup> 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 nonmonotonicity 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, Akerberg 2003, Crawford and Shum 2005). To control for contextual 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 investigate 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 RMB 60.

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.<sup>11</sup> In the baseline, control 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 [RMB 3, 6, 15, 30, or 36] discount, the link below is valid until January 16. . . .” Subjects in this condition were randomly assigned to one of the five 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 [RMB 3, 6, 15, 30, or 36] per each sold ticket to a local charity program [the name of the local charity] that supports poor, elderly people, follow this link. A third party of a prestigious university in China [the name of the top university] will ensure the donations reach the intended recipients. The purchase link below is valid until January 16. . . .” Subjects in this condition were randomly assigned to one of the five 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 [RMB 3, 6, 15, 30, or 36] discount, [wireless provider’s name] will donate [RMB 3, 6, 15, 30, or 36] per each sold ticket to a local charity program [the name of the local charity] that supports poor, elderly people, follow this link. A third party of a prestigious university in China [the name of the top university] will ensure the donations reach the intended recipients. The purchase link below is valid until January 16. . . .” Subjects in this condition were randomly assigned to one of the following 10 offers (discount, donation): (3,3), (3,6), (3,15), (3,30), (6,3), (6,6), (6,15), (15,3), (15,6), or (30,3).

To construct our experimental sample, we began with 15 million subscribers in a large city. From this population, we focused on those mobile subscribers living within two kilometers of one of the theatres playing the movie. By conditioning on proximity to the theatre, we expected to reduce noise associated with heterogeneity in taste based on geographic proximity to a theatre. Given the urban location of the theatres, we therefore targeted our analysis to subscribers with an urban home address. We also conditioned on the subpopulation of subscribers that had purchased a movie ticket using their smartphone during the previous six 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



**Table 1.** Experimental Design and Sample Size for Study 1

Variable	Donation (RMB)					
	0	3	6	15	30	36
<i>Discount (RMB)</i>						
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					

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

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 the 10,500 subscribers who received one of our SMS messages purchased a movie ticket through their smartphone.

## 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 theatres. This movie was selected since the blockbuster potential would guarantee a reasonably 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 RMB 100.

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 were conducted on an individual subject's phone, creating a purely private signaling benefit. Figure 1 indicates the text of the promotional emails sent to subjects.

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 [RMB 20, 35, 50, 60, 75] discount, follow this link..." Subjects in this condition were randomly assigned to one of the five 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 [RMB 5, 10, 15] per each ticket sold to a local charity program [the name of the local charity] that supports poor, elderly people, follow this link. A third party of a prestigious university in China [the name of the top university] will ensure the donations reach the intended recipients..." Subjects in this condition were randomly assigned to one of the three 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 [RMB 20, 35, 50, 60] discount, [wireless provider's name] will donate [RMB 5, 10, 15] per each sold ticket to a local charity program [the name of the local charity] that supports poor, elderly people, follow this link. A third party of a prestigious university in China [the name of the top university] will ensure the donations reach the intended recipients..." Subjects in this condition were randomly assigned to one of the four discount levels and one of the three 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; RMB 0, 20, 35, 50, 60)  $\times$  4 (donation; RMB 0, 5, 10, 15 per ticket sold) between-subjects design. We also included an additional condition with a RMB 75 discount and no donation. The comparison of this condition to a cell with a RMB 60 discount and RMB 15 donation allows us to test for a contextual inference effect. In total, we have 21 groups in this experiment. We oversampled certain cells to ensure sufficient statistical power to test for nonmonotonicity associated with

**Table 2.** Experimental Design and Sample Size for Study 2

Variable	Donation (RMB)			
	0	5	10	15
<i>Discount (RMB)</i>				
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	—	—	—

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



**Table 3.** Summary Statistics

Variable	Obs.	Mean	Std.	Min.	Max.
<i>Purchase indicator</i>	30,300	0.0229	0.150	0	1
<i>Average revenue per user</i> (RMB per month)	30,300	74.109	51.192	8.07	688.98
<i>Monthly data usage</i> (minutes per month)	30,300	633.498	611.451	1	5,647
<i>Number of SMS per month</i>	30,300	365.028	243.656	0	3,099
<i>General packet radio service</i> (Megabytes per month)	30,300	63,885.97	202,239.2	34	1.22E+07

crowding out. Table 2 summarizes the experimental design and the sample sizes in each cell.

Although Chinese regulations 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, the average number of voice minutes used per month, the average number of SMS messages sent and received per month, and the average general packet radio service per month to measure the volume of data usage. Table 3 summarizes this usage behavior.

Table 3 also shows that 694 of the 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 subsampled 40 subjects who purchased a ticket and 40 subjects who did not purchase a ticket. For commercial purposes, the wireless provider oversampled purchasers to obtain feedback on its ticket-buying application. To obtain unbiased survey results, we reweight our survey responses based on the observed purchase and nonpurchase frequencies in each experimental cell. Each of the "nonpurchase" subjects was presented with the survey in Figure 2, consisting of eight questions. An analogous survey was presented to "purchased" subjects, as in Figure 3. 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 RMB 60. 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 0.7% at the 5% significance level.<sup>12</sup> We observe positive and significant effects from "pure discounts" on demand for discounts of RMB 15 or larger. Demand increases by nearly 3 percentage points when the discount is increased from RMB 15 to RMB 30 ( $p < 0.02$ ), although we do not find a significant difference in demand between a discount of RMB 30 and RMB 36. We also observe a positive and significant effect from "pure donations" of at least RMB 30. 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 RMB 3, increasing the discount from RMB 3 to RMB 30 increases demand by over 2 percentage points ( $p < 0.02$ ). However, at higher donation levels, the marginal effect of a discount does appear to decrease. At a discount level of RMB 30, we see demand decrease by almost 2 percentage points when the donation increased from RMB 0 to RMB 3 ( $p < 0.06$ ). This is mild evidence of signal dampening. Yet, 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 (RMB 3 off the regular price) we find a monotonically increasing effect of the charitable donation level on demand. Doubling the donation from RMB 15 to RMB 30 more than doubles demand, in contrast with the finding of a flat effect of charitable donation size documented in Karlan and List (2007).

**Table 4.** Survey Response Rate

Experimental cell		
Discount (RMB)	Donation (RMB)	No. of 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 5.** Experimental Results for Study 1

Variable	Donation (RMB)					
	0	3	6	15	30	36
Discount (RMB)						
0	0.000 (0.000)	0.004 (0.003)	0.006 (0.003)	0.010* (0.004)	0.040** (0.009)	0.046** (0.009)
3	0.006 (0.003)	0.016* (0.006)	0.018* (0.006)	0.020** (0.006)	0.044** (0.009)	—
6	0.008* (0.004)	0.020** (0.006)	0.022** (0.007)	0.024** (0.007)	—	—
15	0.034** (0.008)	0.032** (0.008)	0.028** (0.007)	—	—	—
30	0.062** (0.011)	0.040** (0.009)	—	—	—	—
36	0.066** (0.011)	—	—	—	—	—

Note. Each cell contains the purchase rate across subjects and corresponding standard error (in parentheses) in the specific marketing condition.

\*Significant at the 5% level; \*\*significant at the 1% level.

In Study 1, we see no evidence of the *mere incidence of payments* effect. In some of our campaigns, small discounts as low as RMB 3 increase demand. Comparing no donation (i.e., pure discounts) to a donation level of RMB 3, small discounts appear to work better in the latter than the former case. However, it is the larger (higher-powered) discounts (RMB 15 and RMB 30) that appear less effective when combined with a RMB 3 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 RMB 100. No subjects buy in our base case 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 RMB 0 to RMB 5 increases the purchase probability by 0.429% ( $p < 0.05$ ),<sup>13</sup> from RMB 5 to RMB 10 increases the purchase probability by 0.143% ( $p < 0.35$ ), and from RMB 10 to RMB 15 increases the purchase probability by 0.571% ( $p < 0.13$ ). Raising the discount from RMB 0 to RMB 20 increases the purchase probability by 0.714 percentage points ( $p < 0.02$ ), from RMB 20 to RMB 35 increases the purchase probability by 2.57 percentage points ( $p < 0.01$ ), from RMB 35 to RMB 50 increases the purchase probability by 2.23 percentage points ( $p < 0.02$ ), from RMB 50 to RMB 60 increases the purchase probability by 4.28 percentage points ( $p < 0.36$ ), and from RMB 60 to RMB 75 increases the purchase probability by 2.86 percentage points ( $p < 0.42$ ). A complete set of  $p$ -values corresponding

**Table 6.** Experimental Results for Study 2

Variable	Donation (RMB)			
	0	5	10	15
Discount (RMB)				
0	0.0000 —	0.0043 (0.0025)	0.0057* (0.0028)	0.0114* (0.0040)
20	0.0071* (0.0032)	0.0170** (0.0041)	0.0200** (0.0044)	0.0240** (0.0048)
35	0.0329** (0.0067)	0.0300** (0.0054)	0.0270** (0.0030)	0.0230** (0.0027)
50	0.0557** (0.0087)	0.0420** (0.0063)	0.0180** (0.0024)	0.0160** (0.0023)
60	0.0600** (0.0090)	0.0480** (0.0068)	0.0170** (0.0024)	0.0140** (0.0021)
75	0.0629** (0.0092)	—	—	—

Note. Each cell contains the purchase rate across subjects and the corresponding standard error (in parentheses) in the specific marketing condition.

\*Significant at the 5% level; \*\*significant at the 1% level.

to tests of monotonicity between adjacent cells can be found in Table 7.

We plot the purchase frequencies for each promotional condition in Figure 4. 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 RMB 10. Increasing the discount from RMB 0 to RMB 20 increases the purchase probability by 1.42 percentage points ( $p < 0.01$ ). Similarly, increasing the discount from RMB 20 to RMB 35 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 RMB 35 to RMB 50, the purchase probability falls 0.9 percentage points ( $p < 0.01$ ). If we consider a donation level of RMB 15, increasing the discount from RMB 35 to RMB 50 reduces the purchase probability by 0.7 percentage points ( $p < 0.025$ ). This nonmonotonicity in the effect of price on demand is consistent with our theory of self-signaling.

The line plot in Figure 5 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 nonmonotonicity in the price effect, we also see how price discounts moderate the effectiveness of a charitable donation. For low discount levels of RMB 0 or RMB 20, a small charitable donation (RMB 5 versus RMB 0) increases the purchase probability. However, once the discount is RMB 35 or higher, the rank order of donation effects flips—higher donations decrease the purchase probability. This negative moderating effect of

**Table 7.** Tests for Monotonicity Between Adjacent Cells

Donation	Discount comparisons	Lower $p$ -value (i.e., demand decrease)	Upper $p$ -value (i.e., demand increase)	Donation	Discount comparisons	Lower $p$ -value (i.e., demand decrease)	Upper $p$ -value (i.e., demand increase)
0	0 vs. 20	0.013	0.987	0	0 vs. 5	0.042	0.958
0	20 vs. 35	2.904E-04	1.000	0	5 vs. 10	0.352	0.648
0	35 vs. 50	0.019	0.981	0	10 vs. 15	0.123	0.877
0	50 vs. 60	0.366	0.634	20	0 vs. 5	0.038	0.962
0	60 vs. 75	0.412	0.588	20	5 vs. 10	0.309	0.691
5	0 vs. 20	0.008	0.992	20	10 vs. 15	0.271	0.729
5	20 vs. 35	0.028	0.972	35	0 vs. 5	0.631	0.369
5	35 vs. 50	0.075	0.925	35	5 vs. 10	0.691	0.309
5	50 vs. 60	0.259	0.741	35	10 vs. 15	0.839	0.161
10	0 vs. 20	0.007	0.993	50	0 vs. 5	0.904	0.096
10	20 vs. 35	0.111	0.889	50	5 vs. 10	1.000	8.610E-06
10	35 vs. 50	0.991	0.009	50	10 vs. 15	0.725	0.275
10	50 vs. 60	0.616	0.384	60	0 vs. 5	0.861	0.139
15	0 vs. 20	0.030	0.970	60	5 vs. 10	1.000	2.210E-08
15	20 vs. 35	0.572	0.428	60	10 vs. 15	0.826	0.174
15	35 vs. 50	0.975	0.025				
15	50 vs. 60	0.738	0.262				

Notes.  $P$ -values correspond to two-sample  $t$ -tests of equal means across cells. “Lower” refers to the alternative hypothesis of an increase, and “upper” refers to the alternative hypothesis of a decrease.

discount levels on the marginal effect of a small donation is also consistent with our theory of self-signaling.

Figure 5 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 counterproductive 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. By 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 RMB 35 with a budget of RMB 60.

If we compare a pure discount of RMB 35 to a pure discount of RMB 60, demand increases by 2.7 percentage points ( $p < 0.01$ ). If we instead compare a pure discount of RMB 35 to a combination of a discount of RMB 50 and a donation of RMB 10, we observe crowding out as demand falls 1.5 percentage points ( $p < 0.01$ ). In fact, a pure discount of RMB 75 has a positive effect on demand, whereas crowding out can arise with smaller overall promotion budgets that combine discounts and donations.

As an exploratory exercise, we estimate a simple probit choice model with the main effects and interaction effect of price and donation. The coefficient estimates are reported in Table A.1 in Appendix A. The main effect of price is negative, as one would expect, but the interaction effect between price and donation is positive. As a result, the price elasticity increases with the level of the donation, meaning that consumers become less price sensitive with larger donation amounts. In fact, when the donation level is RMB 15, the model predicts a positive price elasticity, which is consistent with the upward-sloping region of

**Figure 1.** Promotional SMS Message Sent to Subjects in Experiment 2

**SMS in Chinese** “\*\*\*\*看电影做公益活动。购买“X战警：逆转未来”的电影票通兑券，享受[20, 35, 50, 60 RMB]优惠，为本地贫困孤独老人慈善机构\*\*\*\*捐助[5, 10, 15 RMB]，请点击此链接。一所名牌大学\*\*\*\*的第三方将确保捐款达到预期的受益人。”

**SMS in Translation:** 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, and for which [wireless provider’s name] will donate [5, 10, 15 RMB] per ticket to a local charity program [the name of the local charity] that supports poor, elderly people, follow this link; A third party of a prestigious university in China [the name of the top university] will ensure the donations reach the intended recipients”

Figure 2. Survey Questions for Nonpurchasers

### 问卷设计(Survey Design) for NON-purchase 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 Mobile Movie Ticket Buying business. Through this app, yesterday some consumers 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 aged old charity and also discounted the regular ticket price by ZZZ.” Please indicate to what extent you agree with the following statement regarding why these 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 test cells.

(1)是因为想看电影, 有没有折扣和捐赠, 都会购买。

Those consumers 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 those consumers to buy a ticket for the movie.

(3)是因为看重和支持本次捐助活动。

Those consumers value 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。

Those consumers 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?

This SMS 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 themselves think they should care about the poor aged old 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 was an impulse buy for those consumers?

demand we observe in the survey responses. This finding highlights a benefit of our structural self-signaling specification in Section 6.2. The self-signaling specification allows for upward-sloping demand without positive price coefficients (i.e., without consumers with a negative marginal utility of income).

The structural model in Section 6 provides an underlying microeconomic mechanism, “self-signaling,” to explain this positive interaction effect. In our experimental 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 responses. Recall

that survey respondents were sampled from the set of subjects used in the ticket promotion experiment the previous day. A limitation of the survey is that it provides data about the average buyer in a given promotion cell. As we compare survey responses across cells, we are also comparing averages across potentially different groups of consumers since changes in prices and/or donation could change the mix of buyers.

For most of the questions, we find few statistical differences in responses across test cells. However, we do find differences across cells in the average response to the rating of the statement “...wanted to feel good about yourself by donating to the charity,” which was



**Figure 3.** Survey Questions for Purchasers

## 问卷设计(Survey Design) for purchase 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。

You 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 you to buy a ticket for the movie.

(3) 您本次购买, 是因为您看重和支持本次捐助活动。

You value the charity and wanted to support it.

(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。

You wanted to feel good about yourself 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 should care about the poor elderly in need?

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?

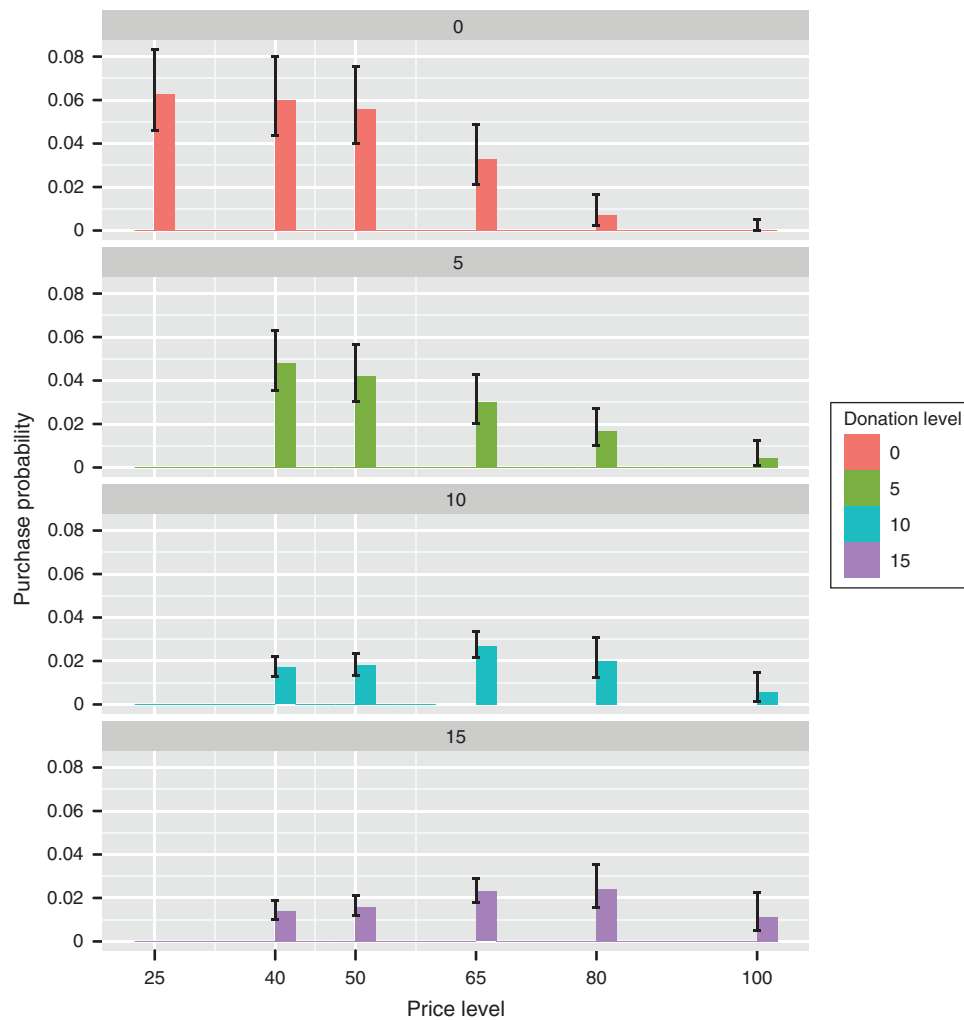
Do you think this purchase was an impulse buy?

measured on an 11-point scale. This question was intended to capture the self-signaling aspect of the purchase. Figure 6 plots the purchase behavior in each of our experimental cells. For those cells with survey respondents, we also plot the corresponding mean self-reported “feel good about yourself” level. Consistent with our theory, the average response changes very little across discount conditions when donation levels are low. Yet, large discounts reduce the rating a lot when donations are relatively high.<sup>14</sup> The decline is significant. The mean rating falls from 9.72 (RMB 15 donation, RMB 35 discount) to 5.34 (RMB 15 donation, RMB 60 discount).<sup>15</sup> The *F*-statistic between

these two cells is 77.1, so we easily reject the null of equal means.<sup>16</sup>

A potential confound is that the correlation between price and the average rating of “feel good about yourself” may be capturing a changing composition of buyers across promotional cells. In Figure C.1, we do observe the average importance of price (i.e., “price sensitivity”) increasing with the size of the discount. Suppose that the self-reported “feel good about yourself” is in fact capturing marginal utility over the donation level itself, possibly through a form of impure altruism associated with the “mere act of donating money” (e.g., Andreoni 1989). Suppose also

**Figure 4.** Purchase Rate Bar Charts for the Donation Levels

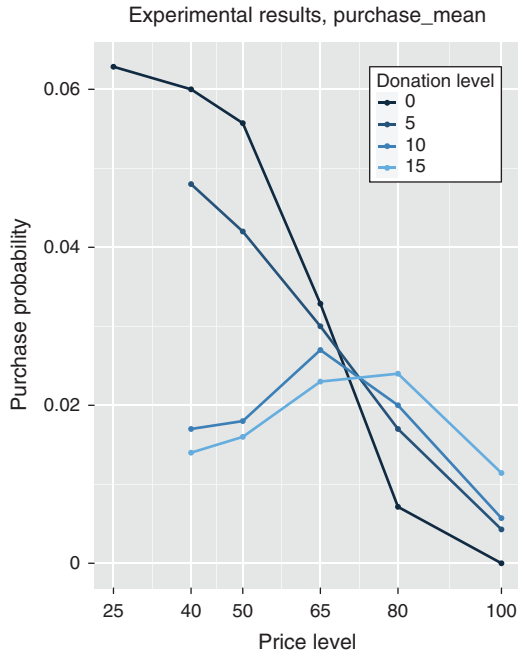


*Notes.* Each bar summarizes the average purchase rate for a price and donation combination. The 95% confidence interval associated with each bar is computed for binomial outcomes.

that the marginal utility over donation levels is negatively correlated with price sensitivity. Then, as price falls, a more price-sensitive and, hence, less donation-sensitive consumer is induced to buy. To rule out this confound, we exploit the fact that our survey respondents are also the purchase subjects from the ticket promotion. So long as the marginal utility of donation levels (i.e., impure altruism) is strictly positive, then it would not be possible for the decline in “feel good about yourself” to be associated with a decline in demand as prices fall. In addition, the other survey responses regarding charity (value for the charity and intentions to donate money in the future) in Figures C.3 and C.4, respectively, seem relatively stable across promotional cells. This stability suggests that the composition of buyers does not seem to be changing much across cells in terms of the average taste for other aspects of the charity.

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 “feel good about yourself” and price-sensitivity levels, the average movie preference in Figure C.2 is flat across price conditions, with an average response of 8.60. However, the mean rating does fall slightly as the charitable donation increases. The mean rating falls from 10.1 (RMB 5 donation, RMB 20 discount) to 8.08 (RMB 15 donation, RMB 20 discount), with an  $F$ -statistic of 12.38. While this might reflect a contextual inference that is specific to the use of prosocial promotions, as opposed to price promotions, a more plausible explanation is that movie tastes are correlated with tastes for donations.

The survey also indicates that the subjects considered the charity itself to be legitimate and worthy. Over 80% of respondents gave a response of at least 8 out of 11, and all of the responses were above 5. The results

**Figure 5.** A Separate Line Plot Is Reported for Each of the Donation Levels in the Experiment

Note. Each point on the line summarizes the average purchase rate across subjects for a given price and donation level.

also indicate that subjects took the survey itself seriously and deliberated over their responses. By contrast with the rating of the charity, when asked “Will you continue donating money to this charity in the future?” the average score was 9.18, with only 44% of subjects giving scores of 7 or less, with some as low as 1. Mean responses are reported in Figure C.4. We also asked subjects to rate the statement “Does this SMS deal seem too good to be true for you?” All of the responses were over 7, but there was almost no difference in responses across cells (the mean ranged from 9.81 to 10.68). 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 5.1 across all cells, including those with discounts of 50% or more off the regular price.

## 6. Model Estimation

### 6.1. A Mathematical Programming with Equilibrium Constraints (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  $h = 1, \dots, H$  denote individual subjects in the experiment. Each subject is randomly assigned to one of  $t = 1, \dots, T$  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

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

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:

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

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 a 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  $\Theta = (\Theta, \Lambda)$  denote all of the structural parameters. Our MPEC estimator maximizes the following objective function:

$$l(\Theta, \delta) = \sum_h [y^h \ln \Pr(y^h = 1 | a_t, p_t; \Theta, \delta_t) + (1 - y^h) \ln (1 - \Pr(y^h = 1 | a_t, p_t; \Theta, \delta_t))], \quad (7)$$

subject to the constraints

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

where

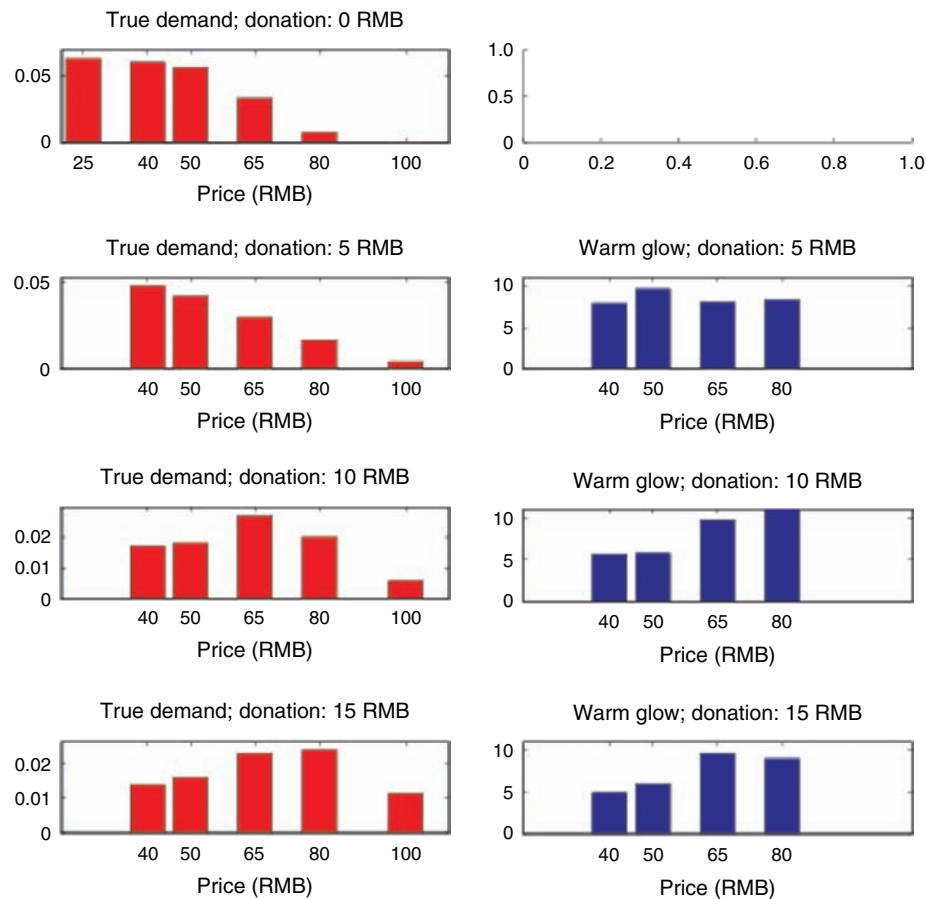
$$\Pr(y^h = 1 | p_t, a_t; \Theta, \delta_t) = \sum_k \Phi(V^k + \gamma a_t + \alpha p_t + \Delta(a_t, p_t, \Lambda)) \omega^k,$$

and

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

We also experiment with a Normal distribution of heterogeneity,  $F(\Theta) = N(\bar{\Theta}, \Sigma_\Theta)$ . Details on the formulation

**Figure 6.** Survey: “Feel Good About Yourself”



*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 item “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.

of the corresponding MPEC estimator are available from the authors on request.

The constraints (8) ensure that our estimated ticket purchase probabilities are exactly consistent with the self-signaling equilibrium implied by Bayes’ rule, where  $\delta_t$  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,  $\delta_t$ . By contrast, a nested fixed-point approach that recomputes the equilibrium beliefs exactly at each iteration of the parameter search over 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 of 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 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. We assume that the probit demand system derives from consumer theory. We therefore assume that  $\alpha^h < 0$  so that consumers cannot have a negative marginal utility of income. If we relax this assumption, it would be possible theoretically to generate nonmonotonic regions in the standard random coefficients probit demand system.<sup>17</sup> In addition, we have assumed there are no income effects, which rules out the theoretical possibility that movies are Giffen goods, which could also generate nonmonotonic demand due to income effects. Bajari et al. (2007) establish the nonparametric identification of the random coefficients distribution,  $\Sigma$ , for discrete choice models with linear indirect utility.

It is well-known in the literature on discrete choice demand with consumer learning that initial prior beliefs are not identified by standard choice data sets



**Table 8.** Structural Estimates and Model Fits

	Probit	RC probit		Self-signaling on $\gamma$		Self-signaling on $\gamma$ and $\alpha$		Self-signaling on $\gamma$ and $V$	
		Comp. 1	Comp. 2	Comp. 1	Comp. 2	Comp. 1	Comp. 2	Comp. 1	Comp. 2
Donation, $\gamma$	−0.022 (0.0031)	−0.0827 (0.0208)	0.2621 (0.147)	−0.2887 (0.1324)	0.0411 (0.0928)	0.0077 (0.0051)	4.6818 (0.7609)	−0.2887 (0.116)	0.0411 (0.1111)
Price, $\alpha$	−0.0063 (0.001)	−0.0137 (0.004)	−0.114 (0.0432)	−0.0163 (0.0022)	−0.0945 (0.0204)	−0.0143 (0.0011)	−1.6336 (0.2969)	−0.0163 (0.0018)	−0.0945 (0.0284)
Intercept, $V$	−1.4373 (0.0581)	−1.2218 (0.1644)	8.1799 (3.1617)	−1.1449 (0.1152)	6.6262 (1.3899)	−1.061 (0.057)	35.1249 (7.2856)	−1.1449 (0.0847)	6.6262 (2.035)
Mixing prob, $\omega$	—	0.981 (0.0017)	—	0.981 (0.0009)	—	0.985 (0.0016)	—	0.981 (0.0011)	—
$\lambda_\gamma$	—	—	—	7.061 (2.8705)	—	9.5845 (0.2504)	—	0.0739 (0.3702)	—
$\lambda_\alpha$	—	—	—	—	—	28.7377 (0.0612)	—	—	—
$\lambda_V$	—	—	—	—	—	—	—	0.296 (0.2292)	—
log-likelihood, $l$	−3,254.09	−3,215.08		−3,208.02		−3,203.45		−3,208.02	
AIC	6,514.17	6,444.16		6,432.04		6,424.89		6,434.04	

Notes. For each model specification, we report point estimates, standard errors (in parentheses), the log-likelihood, and the AIC. For models with heterogeneity, two separate columns are included, one for each mixing component (Comp.). Model fit comparisons can be made based on the AIC. RC, Random coefficients.

(Shin et al. 2012). We follow convention in the literature and assume that consumers have rational expectations so that all consumers have the same beliefs and these beliefs coincide with the population distribution of tastes (see also Erdem and Keane 1996, Ackerberg 2003, Crawford and Shum 2005, Narayanan and Manchanda 2009). Two interesting exceptions are Erdem et al. (2005) and Shin et al. (2012), who elicit consumers' initial beliefs through surveys. Since it is unclear how to design a survey to elicit "self beliefs," we instead use the rational expectations assumption purely for technical reasons. We acknowledge this assumption as a limitation as it is plausible that consumers would have highly subjective and heterogeneous self-beliefs.<sup>18</sup> However, this is a standard limitation of the empirical literature estimating structural discrete choice models with learning. Conditional on this assumption, the diagnostic weights,  $\lambda_\gamma$  and  $\lambda_\alpha$ , are then identified parametrically from the observed nonmonotonic moments in our purchase data. These nonmonotonic moments would not be fit by conventional choice models.

## 6.2. Structural Estimates

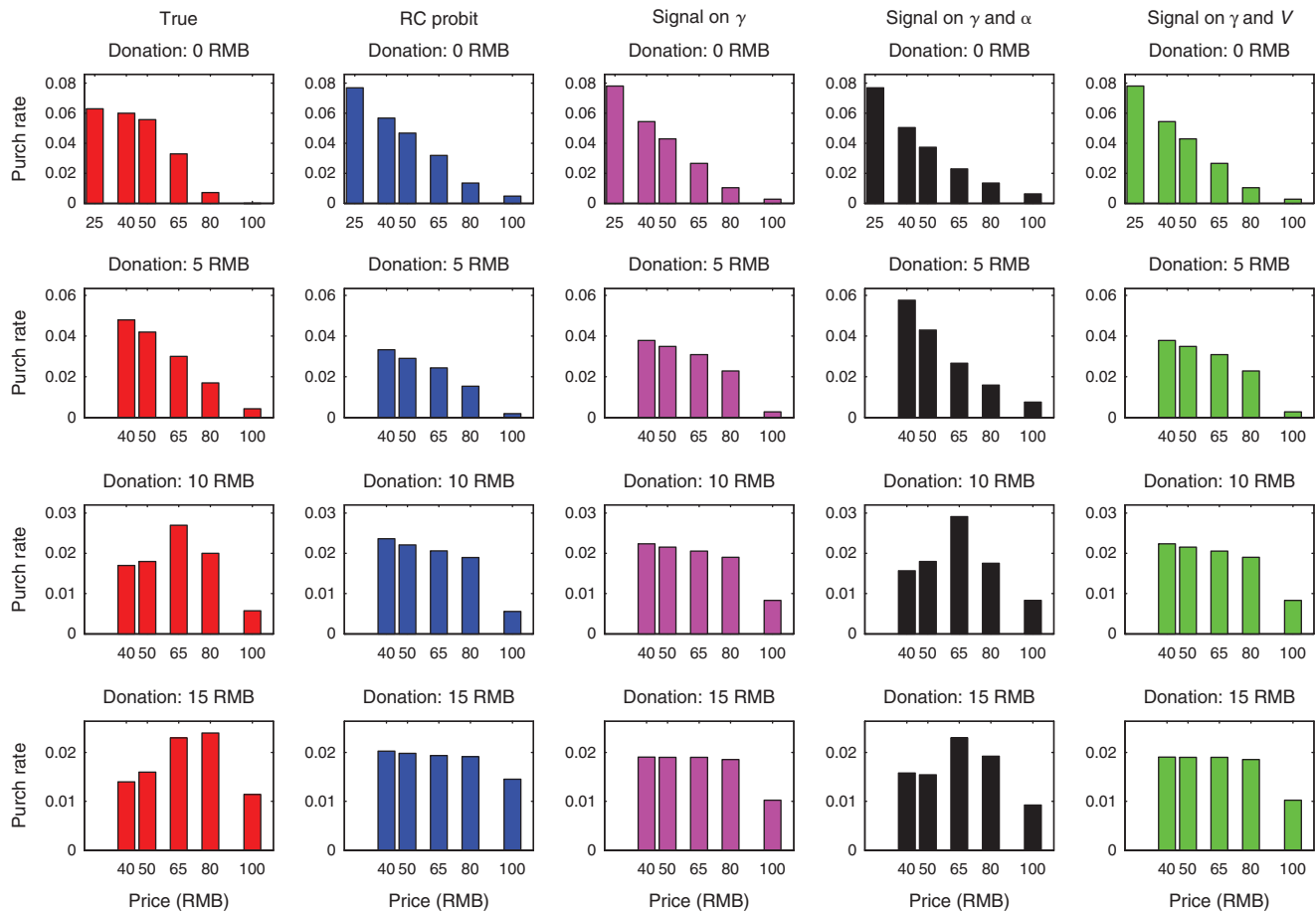
Our three key models consist of the baseline probit, the random coefficients probit, and the random coefficients probit with self-signaling. Table 8 reports the structural parameter estimates of the three models, including three variants of the self-signaling specification. Our self-signaling specifications consists of (1) self-signaling on the taste for donations,  $\gamma$ ; (2) self-signaling on the taste for donations,  $\gamma$ , and the price sensitivity,  $\alpha$ ; and (3) self-signaling on the taste for donations,  $\gamma$ , 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 the fit substantially, as seen by comparing the first two columns. The mixing probability in the second column is 0.98, but is nevertheless significantly different from 1. A standard likelihood ratio (LR) 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 (AIC; final row of Table 8), 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 nonmonotonic effect of prices in the data unless we allow for positive price coefficients. We include these two specifications to capture the baseline behavior we would expect under standard demand theories. 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,  $\lambda_\gamma$  and  $\lambda_\alpha$ , 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 ratio test at conventional significance levels ( $LR = 23.27$ ) $T$ . Thus, we reject the hypothesis of no self-signaling, a joint hypothesis that

**Figure 7.** In-Sample Fit of the Structural Models



Notes. The first column has true shares (red). The second through fifth columns have predicted shares from the random coefficients probit (blue), self-signaling on  $\gamma$  only (magenta), self-signaling on  $\gamma$  and  $\alpha$  (black), and self-signaling on  $\gamma$  and  $V$  (green).

$\lambda_\alpha = \lambda_\gamma = 0$ . We also reject the hypothesis of 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 AIC.

Our best-fitting model with self-signaling on  $\gamma$  and  $\alpha$  is able to fit the nonmonotonic moments in our data in spite of having only two additional parameters than the baseline random coefficients probit. We show this fit in Figure 7. 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  $\gamma$  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. Yet it does not fit the nonmonotonicity. In the fourth column, we show in black the predicted choice behavior from the random coefficients probit with self-signaling on  $\gamma$  and on  $\alpha$ . In the bottom two panels, we see how the self-signaling model is able to fit the nonmonotonic 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  $\gamma$  and on  $V$ . This model is not able to fit the nonmonotonicity in observed choice behavior.

Some of our self-signaling specifications fail to capture the nonmonotonicity in demand. First note that in all of our self-signaling specifications, we find a very large segment that is less price sensitive (higher  $\alpha$ ) than the smaller segment, but with lower taste for movies,  $V$ , and donations,  $\gamma$ . For the specification with self-signaling on  $\gamma$  only, the parameter values imply that it is very hard to send a strong positive signal about  $\gamma$  since only the smaller segment (Comp 2) has a positive, albeit small, marginal consumption utility

for  $\gamma$ . 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  $\gamma$ . Yet, the change in signal is not large enough to deter buyers. Furthermore, higher donation levels actually deter the larger segment from buying, which means that higher donation levels actually improve the self-signal on  $\gamma$  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 7), but does not create a nonmonotonicity. Allowing for self-signaling on both  $\gamma$  and  $V$  does not improve fit since  $\gamma$  and  $V$  are positively correlated across the two segments. Hence, there is little improvement in the ability to manipulate the signal.

By contrast, allowing for self-signaling on both  $\gamma$  and  $\alpha$  improves fit since  $\gamma$  and  $\alpha$  are negatively correlated across 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  $\gamma$  improves, whereas the posterior on  $\alpha$  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  $\gamma$  and  $\alpha$ . The structural coefficient estimates,  $\Gamma$ , in the fourth column of Table 8 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,  $\alpha$ . So, as one might expect, demand slopes downward in the absence of self-signaling. The sensitivity to donations,  $\gamma$ , 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,  $\lambda_\gamma$  and  $\lambda_\alpha$ . Taken at face value, consumers prefer the self-image of getting consumption utility from donations,  $\lambda_\gamma > 0$ . 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).

### 6.3. Robustness

In the previous section, we showed that the self-signaling model fits the data better than a standard probit choice model. We rejected the hypothesis that consumers do not self-signal:  $H_0: \lambda_\alpha = \lambda_\gamma = 0$ . Moreover, we showed that the self-signaling component

of the model fits the nonmonotonic choice behavior observed in the field experiment. A simpler random coefficients probit model with unbounded support over the price coefficients could potentially fit the nonmonotonic choice behavior without self-signaling. We also estimated the random coefficients probit specification with a Normal distribution of taste heterogeneity and a log-Normal distribution of taste heterogeneity. The latter specification restricts the price coefficient to be negative,  $\alpha < 0$ , while allowing for continuously distributed heterogeneity. Neither specification predicts the nonmonotonic demand patterns at the observed price and donation levels. Moreover, both specifications fit the data worse than our self-signaling specification. The AIC values for the Normal and log-Normal random coefficients probit specifications are almost identical, at approximately 6,513.93. By contrast, our self-signaling specification does predict the nonmonotonicity (Figure 7) and has an AIC of 6,432.04 (Table 8). In fact, the discrete random coefficients probit with no self-signaling has an AIC of 6,444.16, which is also superior in fit to the Normal and log-Normal random coefficients specifications. The improved fit of the discrete heterogeneity and its strictly negative estimated support over the price coefficient suggests that positive price coefficients do not provide a good alternative theory for the observed nonmonotonic choice behavior.

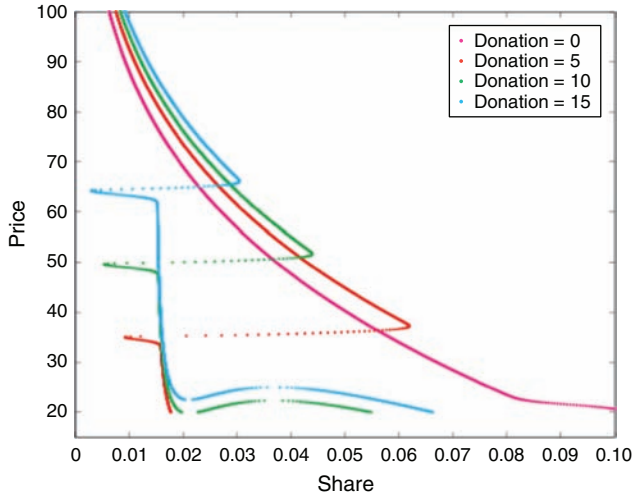
Yet another alternative theory of nonmonotonic choice behavior is that of Giffen goods. A sufficiently large negative income effect could overwhelm the substitution effects associated with price changes, leading to upward-sloping regions of demand. Since we do not observe consumer income, we are unable to include income effects in the demand specification. Although we cannot test this alternative theory, it seems unlikely that movie tickets would be perceived as Giffen goods.

### 6.4. 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  $\gamma$  and  $\alpha$ , 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

**Figure 8.** Equilibrium Choices Under Different Promotional Campaigns



points (see, for instance, Borkovsky et al. 2010).<sup>19</sup> The equilibrium demand correspondences plotted in Figure 8 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.<sup>20</sup>

Figure 8 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 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 counterproductive. Lowering the price raises the consumption utility since the movie is cheaper in the second campaign. Yet, 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 an expected price sensitivity of  $E(\alpha) = 0.0386$ , the RMB 10 discount only raises her consumption utility by 0.386, and hence her total utility declines after the discount. The source of this decline is the multidimensional heterogeneity in consumer tastes. The price decline draws in a 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 multidimensional 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  $\gamma$ . 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  $\gamma$ .

Figure 8 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  $p = \text{RMB } 25.5$  and  $a = 16$ , we find 3 equilibrium share levels: 0.039, 0.034, and 0.0178.

**6.4.1. The Nonfungibility of Promotion Money.** The structural estimates also point toward an interesting nonfungibility 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. Yet out-of-sample, we do not observe consumer choices, and our demand model potentially predicts multiple equilibrium choice probabilities at any given price and donation level,  $(a, p)$ . Aguirregabiria (2011) proposes a homotopy method for counterfactuals that make small changes to the structural parameters of the model under the assumption that there exists a smooth equilibrium selection function. The equilibrium selection function can be approximated at the counterfactual equilibrium of interest by using a Taylor approximation around a “factual” equilibrium that is observed in the data. In



our application, this approach is problematic since the search for an “optimal” price and donation level requires us to predict demand at price and donation levels that are quite different from the levels observed in the data. Consequently, we do not have an obvious candidate “factual” equilibrium for the Taylor approximation at each of the counterfactual points,  $(a, p)$ .

Instead, we experiment with two different equilibrium selection rules. Let  $\mathcal{D}(a, p)$  denote the set of equilibrium posterior beliefs corresponding to a given price level  $p$  and donation level  $a$ . Our first selection rule consists of choosing the most profitable equilibrium from the perspective of the seller

$$\delta(a, p) = \arg \max_{\delta \in \mathcal{D}(a, p)} \{p \times \Pr(y = 1 | a, p; \delta)\}. \quad (9)$$

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

$$\delta(a, p) = \arg \max_{\delta \in \mathcal{D}(a, p)} E\{\max(U)\}, \quad (10)$$

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. Interestingly, the consumer surplus criterion selects the same equilibrium as the binary entropy criterion in 100% of the cases.<sup>21</sup> Hereafter, we use the consumer surplus selection criterion. For those points on the grid that coincide with our observed price and donation levels in-sample, the surplus criterion selects the same equilibrium as the MPEC estimate in 100% of the cases.

Suppose the firm’s objective consists of optimizing expected revenues

$$(p^*, a^*) = \arg \max_{p, a} \{p \times \Pr(y = 1 | a, p)\}. \quad (11)$$

If we restrict donations to be zero,  $a = 0$ , then revenues are maximized at  $p^* = \text{RMB } 20.5$ . However, when we allow  $a > 0$ , then revenues are maximized at  $p^* = \text{RMB } 36.25$  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 9, which plots the expected equilibrium revenue per customer for several alternative promotional campaigns. Recall from Figure 8 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 RMB 30, 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

$$(p^*, a^*) = \arg \max_{p, a} \{a \times \Pr(y = 1 | a, p)\}. \quad (12)$$

**Figure 9.** Equilibrium Revenues Under Different Promotional Campaigns

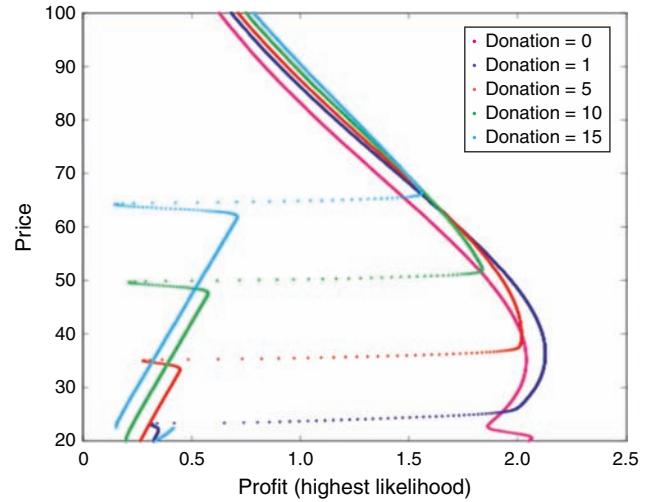
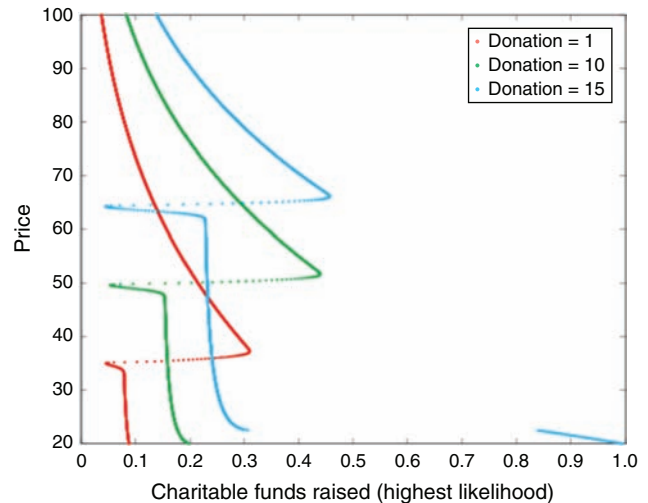


Figure 10 plots the expected equilibrium charitable funds per customer under several campaign scenarios. Once again, we see the effects of crowding out. At higher price levels, a price reduction can increase the expected charitable funds collected. However, large decreases in price can start to become counterproductive 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 8. As a result, the charitable funds-maximizing prosocial campaign sets the price at  $p^* = \text{RMB } 20$  and donations at  $a^* = 16$ . Therefore, the combination of a large donation and a 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

**Figure 10.** Equilibrium Charitable Funds Under Different Promotional Campaigns



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 revenue, a small donation can improve revenue 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. The managerial implications of this analysis are limited by the fact that we do not observe the theatre's box office sales. We cannot measure the long-term effects of this promotion on future demand. The exploration of the long-term effects of self-signaling on theatre demand and profitability would be an interesting direction for future research.

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 et al. 2015).

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 et al. (2012b) provide lab evidence that increasing the costs of the self-signal not only increases its diagnostic value but 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 et al. 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 revenue 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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## Appendix A. Exploratory Probit

**Table A.1.** Exploratory Probit Choice Model Estimates

	Coefficient	Standard error
Intercept	−0.089550592	0.010216333
Donation	−0.01546783	0.001877338
Price	0.001247119	0.000185421
Donation × Price	−0.95760622	0.09791128
Log-likelihood, $l$		−3,221.87
AIC		6,485.02

**Appendix B. Gradients of the MPEC Estimator**

Recall that our MPEC estimator maximizes the log-likelihood function

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

subject to the constraints

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

where

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

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

and

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

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

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

The gradients for the constraints are

$$\begin{aligned} \frac{\partial G_{n1}(\delta_t)}{\partial \theta_j^i} &= - \frac{\Phi(u_t(\Gamma^i, \delta_t)) \omega^i}{[\sum_k \Phi(u_t(\Gamma^k, \delta_t)) \omega^k]^2} \mathbb{I}_{\{j=\gamma\}} \\ &\quad - x_{jt} \left( \left( \theta_n^i \phi(u_t(\Gamma^i)) \omega^i \left[ \sum_k \Phi(u_t(\Gamma^k, \delta_t)) \omega^k \right] \right. \right. \\ &\quad \left. \left. - \left[ \sum_k \theta_n^k \Phi(u_t(\Gamma^k, \delta_t)) \omega^k \right] \phi(u_t(\Gamma^i, \delta_t)) \omega^i \right) \right. \\ &\quad \left. \cdot \left( \left[ \sum_k \Phi(u_t(\Gamma^k, \delta_t)) \omega^k \right]^2 \right)^{-1} \right), \end{aligned}$$

$$\begin{aligned} \frac{\partial G_{n2}(\delta_t)}{\partial \theta_j^i} &= - \frac{(1 - \Phi(u_t(\Gamma^i, \delta_t))) \omega^i}{[\sum_k (1 - \Phi(u_t(\Gamma^k, \delta_t))) \omega^k]^2} \mathbb{I}_{\{j=\gamma\}} \\ &\quad + x_{jt} \left( \left( \theta_n^i \phi(u_t(\Gamma^i, \delta_t)) \omega^i \left[ \sum_k \Phi(-u_t(\Gamma^k, \delta_t)) \omega^k \right] \right. \right. \\ &\quad \left. \left. - \left[ \sum_k \theta_n^k \Phi(-u_t(\Gamma^k, \delta_t)) \omega^k \right] \phi(u_t(\Gamma^i, \delta_t)) \omega^i \right) \right. \\ &\quad \left. \cdot \left( \left[ \sum_k \Phi(-u_t(\Gamma^k, \delta_t)) \omega^k \right]^2 \right)^{-1} \right), \end{aligned}$$

$$\begin{aligned} \frac{\partial G_{n1}(\delta_t)}{\partial \omega^i} &= - \left( \left[ \theta_n^i \Phi(u_t(\Gamma^i, \delta_t)) - \gamma^K \Phi(u_t(\Gamma^K, \delta_t)) \right] \right. \\ &\quad \cdot \left[ \sum_k \Phi(u_t(\Gamma^k, \delta_t)) \omega^k \right] - \left[ \sum_k \theta_n^k \Phi(u_t(\Gamma^k, \delta_t)) \omega^k \right] \\ &\quad \cdot \left[ \Phi(u_t(\Gamma^i, \delta_t)) - \Phi(u_t(\Gamma^K, \delta_t)) \right] \left. \right) \\ &\quad \cdot \left( \left[ \sum_k \Phi(u_t(\Gamma^k, \delta_t)) \omega^k \right]^2 \right)^{-1}, \end{aligned}$$

$$\begin{aligned} \frac{\partial G_{n2}(\delta_t)}{\partial \omega^i} &= - \left( \left[ \theta_n^i \Phi(-u_t(\Gamma^i, \delta_t)) - \gamma^K \Phi(-u_t(\Gamma^K, \delta_t)) \right] \right. \\ &\quad \cdot \left[ \sum_k \Phi(-u_t(\Gamma^k, \delta_t)) \omega^k \right] - \left[ \sum_k \theta_n^k \Phi(-u_t(\Gamma^k, \delta_t)) \omega^k \right] \\ &\quad \cdot \left[ \Phi(-u_t(\Gamma^i, \delta_t)) - \Phi(-u_t(\Gamma^K, \delta_t)) \right] \left. \right) \\ &\quad \cdot \left( \left[ \sum_k \Phi(-u_t(\Gamma^k, \delta_t)) \omega^k \right]^2 \right)^{-1}, \end{aligned}$$

$$\begin{aligned} \frac{\partial G_{n1}(\delta_t)}{\partial \lambda_j} &= -(\delta_{j1t} - \delta_{j2t}) \left( \left( \left[ \sum_k \theta_n^k \phi(u_t(\Gamma^k, \delta_t)) \omega^k \right] \right. \right. \\ &\quad \cdot \left[ \sum_k \Phi(u_t(\Gamma^k, \delta_t)) \omega^k \right] - \left[ \sum_k \theta_n^k \Phi(u_t(\Gamma^k, \delta_t)) \omega^k \right] \\ &\quad \cdot \left[ \sum_k \phi(u_t(\Gamma^k, \delta_t)) \omega^k \right] \left. \right) \\ &\quad \cdot \left( \left[ \sum_k \Phi(u_t(\Gamma^k, \delta_t)) \omega^k \right]^2 \right)^{-1}, \end{aligned}$$

$$\begin{aligned} \frac{\partial G_{n2}(\delta_t)}{\partial \lambda_j} &= (\delta_{j1t} - \delta_{j2t}) \left( \left( \left[ \sum_k \theta_n^k \phi(u_t(\Gamma^k, \delta_t)) \omega^k \right] \right. \right. \\ &\quad \cdot \left[ \sum_k \Phi(-u_t(\Gamma^k, \delta_t)) \omega^k \right] - \left[ \sum_k \theta_n^k \Phi(-u_t(\Gamma^k, \delta_t)) \omega^k \right] \\ &\quad \cdot \left[ \sum_k \phi(u_t(\Gamma^k, \delta_t)) \omega^k \right] \left. \right) \\ &\quad \cdot \left( \left[ \sum_k \Phi(-u_t(\Gamma^k, \delta_t)) \omega^k \right]^2 \right)^{-1}, \end{aligned}$$

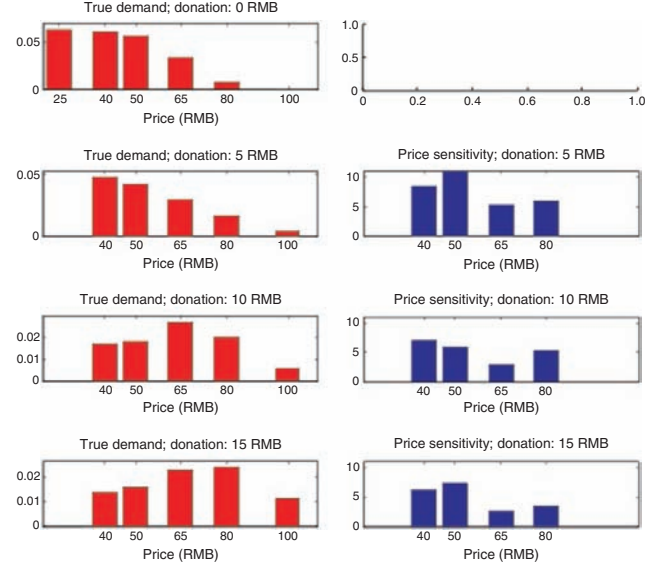
$$\begin{aligned} \frac{\partial G_{n1}(\delta_t)}{\partial \delta_{n1t}} &= 1 - \lambda_n \\ &\quad \cdot \left( \left( \left[ \sum_k \theta_n^k \phi(u_t(\Gamma^k, \delta_t)) \omega^k \right] \left[ \sum_k \Phi(u_t(\Gamma^k, \delta_t)) \omega^k \right] \right. \right. \\ &\quad \left. \left. - \left[ \sum_k \theta_n^k \Phi(u_t(\Gamma^k, \delta_t)) \omega^k \right] \cdot \left[ \sum_k \phi(u_t(\Gamma^k, \delta_t)) \omega^k \right] \right) \right. \\ &\quad \left. \cdot \left( \left[ \sum_k \Phi(u_t(\Gamma^k, \delta_t)) \omega^k \right]^2 \right)^{-1} \right), \end{aligned}$$

$$\begin{aligned} \frac{\partial G_{n2}(\delta_t)}{\partial \delta_{n2t}} &= 1 - \lambda_n \cdot \left( \left( \left[ \sum_k \theta_n^k \phi(u_t(\delta_t, \delta_t)) \omega^k \right] \left[ \sum_k \Phi(u_t(\delta_t, \delta_t)) \omega^k \right] \right. \right. \\ &\quad \left. \left[ \sum_k \theta_n^k \Phi(u_t(\delta_t, \delta_t)) \omega^k \right] \left[ \sum_k \phi(u_t(\delta_t, \delta_t)) \omega^k \right] \right) \\ &\quad \cdot \left( \left[ \sum_k \Phi(u_t(\delta_t, \delta_t)) \omega^k \right]^2 \right)^1, \\ \frac{\partial G_{n1}(\delta_t)}{\partial \delta_{n1t}} &= \lambda_n \left( \left[ \sum_k \theta_n^k \phi(u_t(\delta_t, \delta_t)) \omega^k \right] \left[ \sum_k \Phi(u_t(\delta_t, \delta_t)) \omega^k \right] \right. \\ &\quad \left[ \sum_k \theta_n^k \Phi(u_t(\delta_t, \delta_t)) \omega^k \right] \left[ \sum_k \phi(u_t(\delta_t, \delta_t)) \omega^k \right] \right) \\ &\quad \cdot \left( \left[ \sum_k \Phi(u_t(\delta_t, \delta_t)) \omega^k \right]^2 \right)^1, \\ \frac{\partial G_{n2}(\delta_t)}{\partial \delta_{n1t}} &= \lambda_n \left( \left[ \sum_k \theta_n^k \phi(u_t(\delta_t, \delta_t)) \omega^k \right] \right. \\ &\quad \cdot \left[ \sum_k \Phi(u_t(\delta_t, \delta_t)) \omega^k \right] \left[ \sum_k \theta_n^k \Phi(u_t(\delta_t, \delta_t)) \omega^k \right] \\ &\quad \cdot \left[ \sum_k \phi(u_t(\delta_t, \delta_t)) \omega^k \right] \left( \left[ \sum_k \Phi(u_t(\delta_t, \delta_t)) \omega^k \right]^2 \right)^1, \\ \frac{\partial G_{n1}(\delta_t)}{\partial \delta_{j1t}} &= \lambda_j \left( \left( \left[ \sum_k \theta_n^k \phi(u_t(\delta_t, \delta_t)) \omega^k \right] \left[ \sum_k \Phi(u_t(\delta_t, \delta_t)) \omega^k \right] \right. \right. \\ &\quad \left. \left[ \sum_k \theta_n^k \Phi(u_t(\delta_t, \delta_t)) \omega^k \right] \left[ \sum_k \phi(u_t(\delta_t, \delta_t)) \omega^k \right] \right) \\ &\quad \cdot \left( \left[ \sum_k \Phi(u_t(\delta_t, \delta_t)) \omega^k \right]^2 \right)^1, \\ \frac{\partial G_{n2}(\delta_t)}{\partial \delta_{j2t}} &= \lambda_j \left( \left( \left[ \sum_k \theta_n^k \phi(u_t(\delta_t, \delta_t)) \omega^k \right] \right. \right. \\ &\quad \cdot \left[ \sum_k \Phi(u_t(\delta_t, \delta_t)) \omega^k \right] \left[ \sum_k \theta_n^k \Phi(u_t(\delta_t, \delta_t)) \omega^k \right] \\ &\quad \cdot \left[ \sum_k \phi(u_t(\delta_t, \delta_t)) \omega^k \right] \left( \left[ \sum_k \Phi(u_t(\delta_t, \delta_t)) \omega^k \right]^2 \right)^1, \\ \frac{\partial G_{n1}(\delta_t)}{\partial \delta_{j2t}} &= \lambda_j \left( \left( \left[ \sum_k \theta_n^k \phi(u_t(\delta_t, \delta_t)) \omega^k \right] \left[ \sum_k \Phi(u_t(\delta_t, \delta_t)) \omega^k \right] \right. \right. \\ &\quad \left. \left[ \sum_k \theta_n^k \Phi(u_t(\delta_t, \delta_t)) \omega^k \right] \left[ \sum_k \phi(u_t(\delta_t, \delta_t)) \omega^k \right] \right) \\ &\quad \cdot \left( \left[ \sum_k \Phi(u_t(\delta_t, \delta_t)) \omega^k \right]^2 \right)^1, \\ \frac{\partial G_{n2}(\delta_t)}{\partial \delta_{j1t}} &= \lambda_j \left( \left( \left[ \sum_k \theta_n^k \phi(u_t(\delta_t, \delta_t)) \omega^k \right] \left[ \sum_k \Phi(u_t(\delta_t, \delta_t)) \omega^k \right] \right. \right. \\ &\quad \left. \left[ \sum_k \theta_n^k \Phi(u_t(\delta_t, \delta_t)) \omega^k \right] \left[ \sum_k \phi(u_t(\delta_t, \delta_t)) \omega^k \right] \right) \\ &\quad \cdot \left( \left[ \sum_k \Phi(u_t(\delta_t, \delta_t)) \omega^k \right]^2 \right)^1, \\ &\quad n, j = 1, \dots, J, i = 1, \dots, K. \end{aligned}$$

## Appendix C. Survey Results

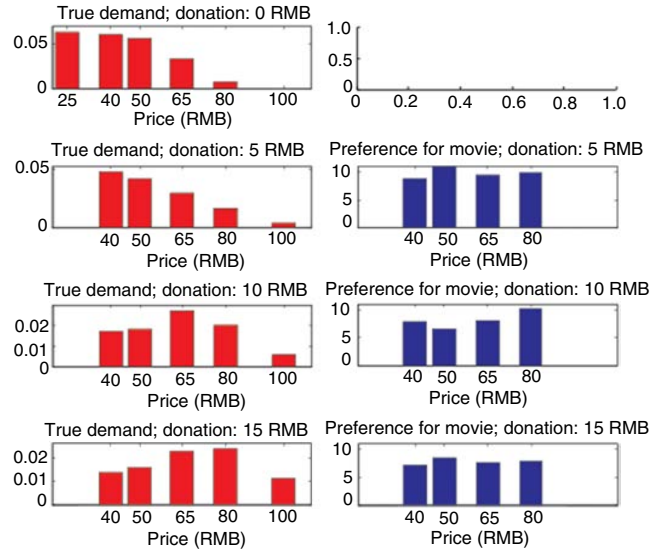
Figures C.1–C.4 include some additional survey results that support our baseline theory of self-signaling.

Figure C.1. Survey: Price Sensitivity



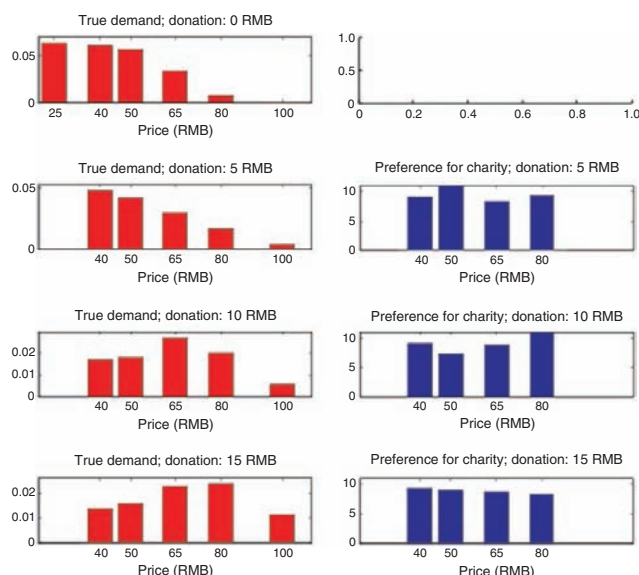
Notes. The left panel reports the average purchase frequencies for each of the 21 campaigns. The right panel reports the average rating of the survey item “the discount was big enough to make it worthwhile for you to buy a movie ticket” as a motivation for buying a ticket corresponding to those campaign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

Figure C.2. Survey: Want to See the Movie

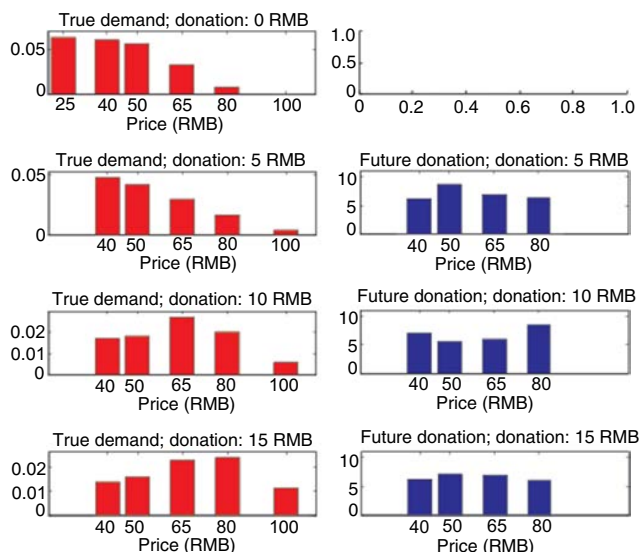


Notes. The left panel reports the average purchase frequencies for each of the 21 campaigns. The right panel reports the average rating of the survey item “you wanted to watch the movie” as a motivation for buying a ticket corresponding to those campaign cells for which we conducted the survey.



**Figure C.3.** 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 item “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 C.4.** 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.

## Endnotes

<sup>1</sup>Kamenica (2012) and Gneezy et al. (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 et al. (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 et al. (2014) fail to detect crowding out effects from financial incentives in a study of Zambian hair-

dressers recruited to sell female condoms for a nongovernmental organization. In other contexts, Gneezy and Rustichini (2000) find that rewards do crowd out schoolchildren'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 et al. (2010) find that small rewards crowd out charitable donations from prior donors, but increase donations of new donors. Barasch et al. (2014) find that monetary incentives crowd out an individual's efficacy in persuading others to donate money.

<sup>2</sup>Interpersonal agency models study principal-agent settings in which the principal has incomplete information about the agent. In a signaling game, the principal can infer something about the agent's private information through the latter's actions.

<sup>3</sup>Intrapersonal agency models study principal-agent settings in which the principal and the agent are the dual selves. In essence, the individual plays a signaling game between her dual selves.

<sup>4</sup>The model builds on the notion of brain modularity and dual-process decision making (see Brocas and Carrillo 2014 for a survey).

<sup>5</sup>An alternative dynamic intrapersonal agency formulation of the decision problem has the judge reflecting back on behavior, which is recalled accurately, but with “imperfect recall” as to the true underlying motivation for the behavior (e.g., Benabou and Tirole 2004, Bernheim and Thomsen 2005). In this case, the decision-making “self” can strategically adjust current behavior to manipulate the signal to the future “self.” Yet another 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).

<sup>6</sup>Our work is similar to Pessemier et al. (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.

<sup>7</sup>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.

<sup>8</sup>Bodner and Prelec (2002) discuss alternative, non-Bayesian learning and belief structures that we do not consider herein.

<sup>9</sup>See Köszegi (2006) and Mobius et al. (2014) for related models in which decisions are driven, in part, by ego utility.

<sup>10</sup>Kamenica (2012) summarizes other experimental evidence that small rewards can be counterproductive.

<sup>11</sup>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, we extracted a sample from the sorted population. This three-step algorithm was integrated into the wireless provider's information technology system.

<sup>12</sup>We use the “cii” function in STATA.

<sup>13</sup>We use the “prtest” routine in STATA to compare differences in sample proportions.

<sup>14</sup>As further evidence of self-signaling, as opposed to social signaling, an average of 1.7 tickets were sold conditional on purchase, indicating that many respondents purchased a single ticket.

<sup>15</sup>Recall that we weight the survey responses to correct for the fact that purchasers were oversampled.

<sup>16</sup>Rerunning 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.

<sup>17</sup>For a price decrease, demand can also decrease if the decrease in expected choice probability for consumers with  $\alpha > 0$  outweighs the increase in expected choice probability for consumers with  $\alpha < 0$ .

<sup>18</sup>In practice, one could conduct a survey to elicit subjects' beliefs explicitly as in Shin et al. (2012).

<sup>19</sup>The smoothness of the model is established through the derivation of the gradients in Appendix B. Regularity is established for almost all solutions through Sard's theorem and the fact that the model is continuously differentiable.

<sup>20</sup>The authors are grateful to Ron Borkovsky for his advice on the properties of the equilibrium correspondence of this model.

<sup>21</sup>The binary entropy criterion has a similar functional form to the likelihood function of the probit model we estimated:  $\delta(a, p) = \arg \max_{\delta \in \mathcal{D}(a, p)} \{\Pr(y = 1 | a, p; \delta) \log(\Pr(y = 1 | a, p; \delta)) + (1 - \Pr(y = 1 | a, p; \delta)) \log(1 - \Pr(y = 1 | a, p; \delta))\}$ .

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## CORRECTION

In this article, “Self-Signaling and Prosocial Behavior: A Cause Marketing Experiment” by Jean-Pierre Dubé, Xueming Luo, and Zheng Fang (first published in *Articles in Advance*, February 2, 2017, *Marketing Science*, DOI:10.1287/mksc.2016.1012), the Borkovsky et al. reference on page 185 has been updated.