Self-Signaling and Pro-Social Behavior: a cause marketing mobile field experiment[1]

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Abstract

We test a self-signaling theory using two large-scale, randomized controlled field experiments. Mobile phone users are randomly sampled to receive promotional offers for movie tickets via SMS technology. Test groups are exposed to different pre-determined levels of price discounts and charitable donations tied to the ticket purchase. The main effects of price discounts and charitable donations increase ticket demand. However, the combination of both discounts and donations can decrease ticket demand. In a post-purchase survey, the same subjects self-report lower ratings of "feeling good about themselves" as the motivation for buying a ticket when discounts and donations are both large. These findings are consistent with a self-signaling theory, whereby the discount crowds out the consumer's "warm-glow" feeling from the charitable donation. Alternative behavioral explanations are ruled out. A structural model of demand with self-signaling is fit to the data using a constrained optimization algorithm to handle the potential multiplicity of equilibria. The estimated preferences reveal that consumers do not derive consumption utility from donations bundled with the ticket. However, they derive significant diagnostic utility: the warm-glow feeling of the self-perception of valuing charitable donations.

Keywords: prosocial behavior, self-signaling, behavioral economics

JEL codes: D4, D81, L00, M31

1 Introduction

The study of pro-social 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. But, starting as early as Deci (1971), cognitive social psychologists have challenged this conventional wisdom. The Cognitive Evaluation Theory argues that if an individual is intrinsically motivated to perform a task, an extrinsic incentive could crowd-out her motivation to perform the task, the so-called *Hidden Costs of Reward* (Lepper and Greene (1978)). A parallel literature in economics has also puzzled over a collection of empirical examples where economic incentives counter-intuitively reduce the motivation for prosocial behavior (e.g. see the survey in Frey and Jegen (2001)). A classic reference is Titmuss (1971) who conjectured that paying blood donors would reduce their incentive to donate blood. However, the empirical evidence of such crowding-out of prosocial behavior in the field has been mixed.[1]

The literature on social image and inference (e.g. Bernheim (1994)) offers one potential explanation for the inconsistent empirical findings of motivation crowding and prosocial behavior. Suppose that peers observe an individual's prosocial actions, but not her underlying preferences. An additional *reputational* motivation can influence prosocial behavior if the individual's actions generate informative signals to peers about her underlying motivation or status (Glazer and Konrad (1996); Benabou and Tirole (2006)). In this case, monetary rewards might weaken the social signal to peers of an individual's altruism, reducing the latter's incentive to behave prosocially for fear of appearing greedy or materialistic. List, Berrens, Bohara, and Kerkvliet (2004) find that social isolation moderates subjects' stated preferences over donations to a non-profit enterprise. Field experiments by Ariely, Bracha, and Meier (2009) and Ashraf, Bandiera, and Jack (2012) find that prosocial behavior increases dramtically 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.

This paper explores the related setting of self-perception, as opposed to social image. Self-perception theory in psychology explores settings where an individual can take the perspective

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

of an outside observer and learn about herself by reflecting on her own actions (Bem (1972)). Bodner and Prelec (2002) incorporate self-perception into a two-component model of preferences with both consumption utility and self-diagnostic utility. Self-diagnostic utility derives from the individual's beliefs about her own preferences. Self-signaling arises when the individual can use her observed actions to update her self-beliefs. A strategic individual may adjust her behavior to manipulate the self signal and improve her diagnostic utility, a form of self-deception that has been documented in both laboratory and field experiments (Quattrone and Tversky (1984); Shafir and Tversky (1992); Dhar and Wertenbroch (2012); Gneezy, Gneezy, Riener, and Nelson (2012); Savary, Goldsmith, and Dhar (2014)). Benabou and Tirole (2006) explore the formal game theory of self-signaling in the context of prosocial behavior, modeling behavior and the corresponding self signal as equilibrium outcomes. A self-diagnostic motivation for behaving prosocially emerges when the behavior raises diagnostic utility, conveying a *warm-glow* feeling. Extrinsic monetary incentives may be counterproductive and crowd out prosocial behavior if they dampen the self signal and reduce the warm-glow feeling.

We add to this literature by conducting two large-scale, controlled field experiments to test self-signaling. We also measure the potential incompatibility between self-image motivation and extrinsic financial incentives to behave prosocially.[2] Like Gneezy, Gneezy, Riener, and Nelson (2012), we study consumer demand for a product with a prosocial characteristic. The experiments were conducted in a large Chinese city in collaboration with one of the world's largest mobile carriers. We randomly sampled subjects from a population of mobile subscribers who own a smartphone and live close to a movie theater. Each subject was randomly assigned to one of several promotional campaigns for a movie ticket, and was then contacted via SMS with the offer. One set of test cells consisted of "pure discounts" off the regular price of a ticket. A second set of cells consisted of "pure donations" of a pre-determined magnitude to a specific charity that would be made in conjunction with each ticket purchased. A third set of test cells consisted of a combination of a discount and a charitable donation. We observe each subject's purchase decision. In the second experiment, we also conducted a follow-up survey with a subset of the subjects twenty-four hours after the promotional experiments. We asked each subject a series of motivation-related questions. Since the receipt of the SMS message and the resulting purchase decision are all performed on an individual subject's mobile phone, 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. The use of donations triggers the self-signaling motive. Discounts can dampen the

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

signal, or warm-glow feeling, thereby reducing the diagnostic motivation to buy a ticket. If the dampening crowds out ticket purchases, we expect to observe regions of upward-sloping demand. As expected, in the absence of a donation, we find that discounts increase demand. When we combine discounts and donations, we find non-monotonicities that are consistent with the self-signaling theory. For relatively small donations, discounts increase demand. However, for even moderate-sized donations, we see a non-monotonic effect of discounts on ticket sales, which is consistent with a dampening of the self signal. Our survey corroborates the self-signaling theory. At 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 (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)). Holding the total promotion budget fixed, crowding out arises from the allocation of the budget across discounts and donations, not from the total size of the budget.

We also use our experimentally-generated data to estimate the structural form of our model of demand, which nests the self-signaling equilibrium. The estimator we use is robust to the potential multiplicity of equilibria that can emerge. Similar to DellaVigna, List, and Malmendier (2012), we use the structural estimates of consumer preferences to describe and quantify the underlying motivation. We find that the average consumption utility from donations is statistically insignificant, albeit very imprecisely measured. However, consumers place a statistically and economically insignificantly positive weight on the perception of a high marginal utility from donations. At face value, the average consumer gets no consumption benefit from the charitable donation, but does value the self-perception of being altruistic. This finding is qualitatively similar to List (2006) who finds that, in the field, individuals are motivated by reputation and not by social preferences. Interestingly, consumers in our study also appea to place significant negative weight on their perception of price sensitivity, perhaps because they feel satisfaction from the self-perception of finding a good deal.

The remainder of the paper is organized as follows. In section 2, we discuss the relationship of our work to the theory and practice of cause marketing. In section 3 we discuss the structure of our field experiments and the data we collected. Section 4 develops the model of self-signaling and the corresponding consumer demand. We then conduct model simulation to develop the crowding out result and to illustrate the potential multiplicity of equilibria. Alternative theories of crowding out are also discussed. The estimator for the structural form of the model is discussed in section 5. Our empirical results are summarized in section 6. We then 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)). Cause marketing has become an increasingly popular marketing tactic in recent years, with total US spending increasing each year since at least 2005 and reaching $1.78 billion in 2009.[3] Conventional wisdom about cause marketing campaigns holds that consumer willingness-to-pay is increasing weakly in the donation size (e.g. Arora and Henderson (2007); Haruvy and Leszczyc (2009); Elfenbein and McManus (2010); Koschate-Fischer, Stefan, and Hoyer (2012)). Industry experts share this view, advising firms that more sponsorship raises consumer support. Cause marketing consultant Paul Jones explains "Cause marketing works because people have an affinity for the cause or the cause's mission and want to support it.[4]" The underlying logic is that experts believe consumer response to cause marketing reflects altruism.

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

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

3 Data

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

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

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

3.1 Study 1

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

Our experimental context consisted of a mobile SMS offer for a general admission voucher for any 2D movie showing between January 15, 2014 and January 31, 2014. The offer was pushed to subjects' mobile phones 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 are conducted on an individual subject's phone, creating a purely private signaling benefit.

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

To construct our experimental sample, we begin with the 15 million subscribers in a large city. From this population, we focus on those mobile subscribers living within 2 kilometers of one of the theaters playing the movie. By conditioning on proximity to the theater, we expected to reduce

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

noise associated with heterogeneity in taste based on geographic proximity to a theater. Given the urban location of the theaters, we therefore target our analysis to subscribers with an urban home address. We also conditioned on the sub-population of subscribers that had purchased a movie ticket using their mobile phone during the previous 6 months. This condition ensured that the subscriber had a smart phone (i.e. that could be used to purchase a movie ticket) and that the subscriber had potential interest in a mobile purchase offer. From this overall target population of 1 million, we randomly sampled 10,500 mobile subscribers to whom the wireless provider pushed one of our promotional SMS messages.

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

3.2 Study 2

This promotional field experiment was conducted with a corporate partner that is one of the largest wireless service providers in the world. We coordinated the experiment with the Chinese release of the movie *X-Men: Days of Future Past*, on May 23, 2014 in IMAX theaters. This movie was selected since the blockbuster potential would guarantee a reasonably high baseline rate of interest in tickets, giving us sufficient statistical power. The movie was released only in a 3D version, with a regular ticket price of 100 RMB.

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

Subjects were randomly assigned to one of several promotional conditions. In the baseline control condition, the mobile ad SMS read: "To buy a voucher for general admission to any of X-Men: Days of Future Past's 3D showings, follow this link..." In the pure discount condition, the SMS read: "To buy a voucher for general admission to any of X-Men: Days of Future Past's 3D showings at a [20, 35, 50, 60, 75 RMB] discount, follow this link..." Subjects in this condition were randomly assigned to one of the 5 discount levels. In our pure donation condition, the SMS read:

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

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

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

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

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

Finally, on May 23, 2014, the day after the SMS expired, we conducted a follow-up telephone survey. For each of 12 of our 21 experimental cells, we randomly sub-sampled 40 of our subjects who purchased a ticket and 40 of our subjects who did not purchase a ticket. Each of the "not purchased" subjects was presented with the survey in Figure 1, consisting of 8 questions. An analogous survey was presented to "purchased" subjects. Response rates are summarized in Table 4. Response rates varied from 23 to 35 across the cells.

4 A Model of Self-Signaling

4.1 Model

In this section, 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 pro-social characteristic, a pre-determined donation amount to a charity, and a discount off the regular price. The consumer's consumption utility consists of the direct benefit from the movie ticket net of the price and, when applicable, the direct benefit from a charitable donation level. The direct benefit from a charitable donation may reflect genuine altruism and/or the joy of giving itself.[6] In addition, the consumer has a prior belief about her preferences before receiving the promotional offer. The consumer derives diagnostic utility based on her posterior self-beliefs after making her purchase decision in response to the promotional offer. The 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.[7] 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's ticket demand maximizes total utility, which combines the consumption and diagnostic components.

Consider a population of consumers indexed $h = 1, ..., H$. Let V^h denote consumer $h's$ consumption value of the movie. Let $p \geq 0$ 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 $y^h \in \{0, 1\}$ where 1 denotes purchase and 0 denotes non-purchase.

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

$$U^h = \begin{cases} \left(V^h + \alpha^h p + \gamma^h a\right) + \mathbb{I}_{\{a>0\}} R\left(a, p, \Lambda, 1\right) & , y^h = 1 \\ \mathbb{I}_{\{a>0\}} R\left(a, p, \Lambda, 0\right) & , y^h = 0 \end{cases} \tag{1}$$

where $\Theta^h = \left(V^h, \alpha^h, \gamma^h\right)$ are utility parameters. The first utility component, $\left(V^h + \alpha^h p + \gamma^h a\right)$, denotes the net consumption utility of the offer. The second term,

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

[6] 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.

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

denotes the consumer's diagnostic utility, where $\Lambda = \left(\lambda_\gamma, \lambda_\alpha\right)$ are diagnostic utility weights that we assume are common across consumers. The term $\mathbb{I}_{\{a>0\}}$ indicates whether or not a charitable donation is attached to the ticket and, hence, whether there is a potential role for self-perception in the purchase decision. Diagnostic utility becomes triggered when there is a prosocial charitable motivation for buying a ticket, i.e. $a > 0$. In the absence of a donation, the consumer only derives consumption utility. The posterior expectation of α and γ are conditional on the observed terms of the marketing campaign and the consumer's own observed action. Bodner and Prelec (2002) interpret 1 as a two-period utility function. In the first period, the consumer obtains consumption utility from her purchase decision. In the second period, the consumer derives diagnostic utility from her self-perception. The consumer makes her purchase decision to maximize this total (two-period) utility. Our empirical analysis will focus only on the actual purchase decision and not on the inrapersonal dynamics.

The consumer purchases the ticket if

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

The term $\Delta(a, p, \Lambda) = \mathbb{I}_{\{a>0\}} \left[R(a, p, \Lambda, 1) - R(a, p, \Lambda, 0)\right]$ captures the *warm glow* feeling from supporting a cause marketing campaign. The degree of *warm glow* does not reflect the signaling benefit of buying per se, but rather the relative benefit of buying versus not buying.

To complete the model, we need to specify the consumer's prior beliefs before responding to the campaign. We assume consumers have rational expectations, such that their prior beliefs are mutually consistent and coincide with the true population distribution of tastes. Following the convention in most of the microeconomic literature on learning, we assume a Normal prior belief:

$$\Theta^h \quad \sim \quad N\left(\left[\begin{array}{c} \bar{\gamma} \\ \bar{\alpha} \\ \bar{V} \end{array}\right], \left[\begin{array}{ccc} \sigma_\gamma^2 & 0 & 0 \\ 0 & \sigma_\alpha^2 & 0 \\ 0 & 0 & \sigma_V^2 \end{array}\right]\right). \tag{4}$$

The off-diagonal covariances in 4 are restricted to zero for econometric parsimony, but could in principle be left unrestricted. It is straightforward to apply Bayes' rule to derive the consumer's posterior beliefs after making her purchase decision:

$$E\left(\Theta_k | y, a, p\right) = \bar{\Theta}_k + (-1)^{(1-y)} \sigma_{\Theta_k} \int\int \frac{\phi\left(\frac{-\frac{V+\Theta_l x_l + \Delta(a,p,\Lambda)}{x_k} - \bar{\Theta}_k}{\sigma_{\Theta_k}}\right)}{\Phi\left((-1)^y \frac{-\frac{V+\Theta_l x_l + \Delta(a,p,\Lambda)}{x_k} - \bar{\Theta}_k}{\sigma_{\Theta_k}}\right)} f\left(\Theta_l, V\right) d\Theta_l dV, \quad k, l \in \{\gamma, \alpha\}, \; k \neq l.$$

See Appendix A for a derivation. We write the system of posterior expectations more compactly as:

$$E\left(\Theta|a,p\right)=F\left(\bar{\Theta},\Sigma_{\Theta},a,p\right). \tag{5}$$

If we follow the convention in the demand estimation literature and let $V^h \sim N\left(\bar{V},1\right)$, then we have the classic random coefficients multinomial probit model of choice. The expected probability that consumer h purchases a movie ticket is

$$Pr\left(y^h=1|p,a\right) \quad =\int Pr\left(\bar{V}+\alpha p+\gamma a+\Delta\left(a,p,\Lambda\right)>0\right)f\left(\alpha,\gamma\right)d\alpha d\gamma \tag{6}$$

where Φ is the CDF of a standard Normal random variable and $f\left(\alpha,\gamma\right)$ is a bivariate Normal density. A complication in the estimation of 6 is that it nests the computation of the warm-glow feeling, $\Delta\left(a,p,\Lambda\right)$, which is a fixed-point of the system of posterior beliefs, 5. That is, we need to compute the consumer's self-signaling equilibrium beliefs in order to derive her expected demand.

An equilibrium to the self-signaling model consists of posterior beliefs $E\left(\Theta|a,p\right)$ that satisfy Bayes' Rule, 6. Since we cannot express the posterior beliefs in closed form, we need to find roots of the system 5 numerically. As we illustrate with a numerical exampl in the next section, a multiplicity of equilibria can exist for a given promotional offer (a,p).

4.2 Model Simulations

In this section, we conduct model simulations with specific parameter values to illustrate how prices and donations moderate individual choice behavior under self-signaling. We also illustrate the potential for the emergence of multiple equilibria, which will influence our choice of estimator when we fit the model to the data. Since the heterogeneity in the model has unbounded support, the resulting equilibrium purchase behavior will always be at least partially separating. A true pooling equilibrium would require a self-signal of $\pm\infty$ to push the expected probability of purchase to 0 or 1.

For illustrative purposes, assume the regular ticket price is 7 and assume the following parameter values for population tastes:

- $\bar{\Theta}=\begin{bmatrix}\bar{\gamma}\\ \bar{\alpha}\\ \bar{V}\end{bmatrix}=\begin{bmatrix}1\\ -0.9\\ -0.3\end{bmatrix}$
- $\Sigma_{\Theta}=\begin{bmatrix}0.3 & 0 & 0\\ 0 & 0.3 & 0\\ 0 & 0 & 1\end{bmatrix}$

- $\Lambda = \left(\lambda_\gamma, \lambda_\alpha\right) = (0.5, 0.1)$.

These values were chosen to generate a relatively low baseline purchase rate, $Pr(y = 1, a = 0, p = 7) = .01$, where $a = 0$ and $p = 7$ (no discount), which matches our experience in the field. The assumed values for Λ imply that consumers prefer a self-image of high altruism (pure or impure) and low price-sensitivity. In practice, the literature on prosocial behavior would predict that the true $\lambda_\gamma > 0$; but we do not per se have any prior on the sign or magnitude of λ_α. In our setting where the donation is bundled with a promoted ticket price, it is possible that consumers have $\lambda_\alpha < 0$ if they value the perception of being good at finding deals, for instance.

We numerically compute the equilibrium beliefs and choice behavior for a grid of donation and price levels: $a \in [0, 3]$ and $p \in [2, 7]$. For each grid point, we use 1000 independent random starting values to compute the equilibrium. For most of the points, we find a unique equilibrium across our start values. However, for cases with relatively low donation levels and high prices, we often find two very distinct equilibria. We never find more than two equilibria for these parameter values. In the cases with two equilibria, one has a very high purchase probability near 1, with very little self-learning from purchase and high self-learning from non-purchase. The second equilibrium has a very low purchase probability, with high self-learning from purchase and low self-learning from non-purchase. We plot the equilibrium choice probabilities along our grid in Figure 3. Each curve represents choice behavior corresponding to a specific donation level. Movement along the curve corresponds to different price discounts, holding the donation fixed. For small donation levels of 0.6 and 0.9, we find two equilibrium choice outcomes at each discount and donation pair. In each case one of the equilibrium paths is an "almost" pooling equilibrium in the sense that choice behavior is close to the 0 or 1. For instance, when $a = 0.9$, one of the two equilibria appears to move towards 100% purchase as the discount declines towards zero. However, at higher levels of donation, we find a unique equilibrium choice behavior for each discount level. This potential for multiplicity will need to be addressed when we develop our estimator for the structural form of the model.

We plot the corresponding purchase probability function in Figure 4. For grid points with multiple equilibria, we select the choice behavior corresponding to a low choice probability since it generates a smoother-looking purchase probability function over the entire grid. This assumption also matches our empirical data where purchase probabilities are less than 10%. For our assumed parameter values, we observe crowding out at relatively low levels of donation as higher discounts lead to lower purchase rates. However, as we move away from the origin, higher discounts start to increase demand. These findings are consistent with those of Benabou and Tirole (2006). Table 7 illustrates crowding out by comparing two promotional campaigns, each with the same donation size of $a = 0.5$. In the first campaign, $(0.5, 2.5)$, the net price is 2.5 (a discount of 4.5), whereas the second campaign, $(0.5, 2)$, has a lower price of 2 (discount of 5). Even though the second

campaign has a lower price, it generates fewer ticket sales with an overall response rate of 0.0353, compared with 0.043 in the first campaign. At $a = 0.5$, a price discount is counter-productive. This is because the discount reduces the overall net diagnostic utility from $\Delta(0.5, 2.5, \Lambda) = 0.6393$ to $\Delta(0.5, 2, \Lambda) = 0.6089$. Most of this loss in diagnostic utility comes from the dampening of the signals on $E(\gamma|y = 1)$ and $E(\alpha|y = 0)$ respectively. Increasing the price discount reduces the posterior self-perception of γ when a ticket is purchased. It also increases the posterior perceived magnitude of α when a ticket is not purchased. Both these effects reduce diagnostic utility, leading to a lower incentive to purchase. In this case, the net consumption benefits of the lower price are overwhelmed by the loss in diagnostic utility.

4.3 Alternative Explanations

Past work has discussed alternative mechanisms that could also lead to a crowding out of motivation and, hence, of pro-social 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.[8] This discontinuous shift could also be consistent with a self-perception theory like the one we investigate. To construct a test between a "mere incidence of payment" theory and self-signaling, we exploit the fact that under self-signaling, crowding out need not arise as a discontinuity at very small reward levels per se. Rather, we may observe non-monotonicity in the effect of a reward whereby small rewards increase demand and larger rewards reduce demand. A direct test can also be constructed by surveying consumers about their warm-glow feeling under different promotional settings.

Benabou and Tirole (2003) derive motivation crowding from a theory of "contextual inference," whereby the consumer learns about the task itself rather than about herself. In our experiments, a consumer may interpret a promotion as an ex ante signal about the underlying quality of the movie, with an aggressive promotion signaling low quality. This type of product learning differs from most of the past empirical work on product uncertainty where consumers learn ex post through their consumption experiences after the purchase (Erdem and Keane (1996); Ackerberg

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

(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.

5 Model Estimation

We now discuss an estimator of the structural parameters of the model in section 4. The potential multiplicity of self-signaling equilibria for the model raises the well-known coherency problem with maximum likelihood estimation (Tamer (2003)). We use the constrained optimization approach proposed in Su and Judd (2012) to obtain consistent, maximum likelihood estimates.

Let y_t^h be an indicator variable denoting whether consumer h purchases a ticket or not when confronted with a promotional offer (a_t, p_t), where $t \in \mathrm{T}$ indexes the set of promotional offers tested in the mobile experiment. Finally, let the parameter $\delta_{tky} = E(\Theta_k | a_t, p_t, y)$ denote the posterior expectation about taste coefficient Θ_k conditional on promotional state (a_t, p_t) and purchase state y. Our MPEC estimator maximizes the following objective function:

$$\mathscr{L}(\Theta, \Lambda, \delta) = \sum_h y_t^h log\left(Pr\left(y_t^h = 1 | p_t, a_t; \Theta, \Lambda, \delta_t\right)\right) \tag{7}$$

subject to the constraints

$$\delta_t = F(\Theta, \Lambda, a_t, p_t), t = 1, .., T \tag{8}$$

and where

$$Pr\left(y_t^h = 1 | p_t, a_t; \Theta, \Lambda, \delta_t\right) = \int \Phi\left(\bar{V} - \alpha p_t + \theta a_t + \lambda_\gamma\left[\delta_{\gamma 1t} - \delta_{\gamma 2t}\right] + \lambda_\alpha\left[\delta_{\alpha 1t} - \delta_{\alpha 2t}\right]\right) f(\alpha, \gamma) d\alpha d\gamma.$$

The constraints, 8, ensure that our estimated ticket purchase probabilities are exactly consistent with the self-signaling equilibrium implied by Bayes' rule. This formulation yields an objective function that is smooth in the equilibrium beliefs, δ. Note that a nested fixed-point approach that re-computes the equilibrium beliefs exactly at each iteration of the parameter search over Θ would produce an objective function that is potentially discontinuous in the structural parameters. Another advantage of the MPEC approach is that we do not need to solve repeatedly for all the equilibria for each step of the parameter search. Su (2014) demonstrates that the objective function 7 is equivalent to integrating the objective function over a probability distribution for the countable set of potential equilibria to the model and where the probability is deterministically equal to 1 for the equilibrium with the highest likelihood. If we also assume that the same equilibrium is always played in a given promotion state, then our MPEC estimates of $(\Theta, \Sigma, \Lambda)$ are equivalent to the maximum likelihood estimates.

The identification of most of the model parameters follows from the usual econometric theory for discrete choice models estimated with cross-sectional data. Bajari, Fox, and Ryan (2007) establish the nonparametric identification of the random coefficients distribution, Σ, for discrete choice models with linear indirect utility. We also use the conventional normalization that $\sigma_V = 1$ and, for practical purposes, we restrict all the random coefficients to be uncorrelated. The diagnostic weights, Λ, are then identified parametrically from the observed non-monotonic moments in our purchase data. These moments would not be fit by conventional choice models.[9]

6 Experimental Results

6.1 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. Surprisingly, no subjects buy in our base case with no promotional offer; although given the discrete nature of our data, we cannot rule out a purchase probability of as high as 0.007% at the 5% significance level.[10] We observe positive and significant effects from "pure discounts" on demand for discounts of 15 RMB or larger. Demand increases by nearly 3 percentage points when the discount is increased from 15 RMB to 30 RMB (p<.02); although we do not find a significant difference in demand between a discount of 30 RMB and 36 RMB. We also observe a positive and significant effect from "pure donations" of at least 30 RMB. When we combine discounts and donations, all of our point estimates are monotonically increasing in the level of discounts. For instance, at a donation

[9] Monte Carlo experiments demonstrating the recoverability of the model parameters in small samples are available upon request.

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

level of 3 RMB, increasing the discount from 3 RMB to 30 RMB increases demand by over two percentage points (p<.02). However, at higher donation levels, the marginal effect of a discount does appear to decrease. At a discount level of 30 RMB, we see demand decrease by almost two percentage points when the donation increased from 0 RMB to 3 RMB (p<0.06). This is mild evidence of signal dampening. But, the decline is not very precise and, at a 5% significance level, we cannot rule out a demand increase of half a percentage point. Interestingly, when the discount is low (3 RMB off the regular price) we find a monotonically increasing effect of the charitable donation level on demand. Doubling the donation from 15 to 30 RMB more than doubles demand, in contrast with the finding of a flat effect of charitable donation size documented in Karlan and List (2007).

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

6.2 Experimental Data for Study 2

We tabulate our experimental data in Table 6. 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 0.526% 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 measured imprecisely. Increasing the donation from 0 RMB to 5 RMB increases the purchase probability by 0.429% (p<0.05);[11] from 5 RMB to 10 RMB increases the purchase probability by 0.143% (p<.35); and from 10 RMB to 15 RMB increases the purchase probability by 0.571% (p<0.13). Raising the discount from 0 RMB to 20 RMB increases the purchase probability by 0.714% (p<0.02); from 20 RMB to 35 RMB increases the purchase probability by 2.57% (p<0.01); from 35 RMB to 50 RMB increases the purchase probability by 2.23% (p<0.02); from 50 RMB to 60 RMB increases the purchase probability by 4.29% (p<0.36); and from 60 RMB to 75 RMB increases the purchase probability by 2.86% (p<0.42).

We plot the purchase frequencies for each promotional condition in Figure 5. Results are presented by donation level. All of our discount levels generate a positive and statistically significant lift in purchase probability relative to the baseline case of no discount. However, it is not always the case that a larger discount increases demand. Consider the promotion conditions with a donation level of 10 RMB. Increasing the discount from 0 RMB to 20 RMB increases the purchase

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

probability by 1.42 percentage points (p<0.01). Similarly, increasing the discount from 20 RMB to 35 RMB increases the purchase probability by 0.7 percentage points (p<0.12); although here we cannot rule out "no change" at the 5% significance level. However, if we increase the discount from 35 RMB to 50 RMB, the purchase probability falls 0.9 percentage points (p<0.01). If we consider a donation level of 15 RMB, increasing the discount from 35 RMB to 50 RMB reduces the purchase probability by 0.7 percentage points (p<0.025). This non-monotonicity in the effect of price on demand is consistent with our theory of self-signaling.

The line plot in Figure 6 makes it easier to compare relative magnitudes of the promotional conditions. The plot illustrates the negative complementarity between the two promotion formats, discounts and donations, on purchase behavior. In addition to the non-monotonicity in the price effect, we also see how price discounts moderate the effectiveness of a charitable donation. For low discount levels of 0 RMB or 20 RMB, a small charitable donation (5 RMB versus 0 RMB) increases the purchase probability. However, once the discount is 35 RMB or higher, the rank order of donation effects flips – higher donations decrease the purchase probability. This negative moderating effect of discount levels on the marginal effect of a small donation is also consistent with our theory of self-signaling.

Figure 6 also shows that the crowding out of demand is not simply a "mere incidence of payment" effect. For high donation levels, small discounts in fact increase demand and the discount only becomes counter-productive at larger levels of 50% off or more.

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

In our setting, there is no obvious way to construct a direct test of self-signaling that manipulates whether or not a consumer has a reputational motivation (e.g. List (2006)). Instead, we use the survey. Recall that survey respondents were sampled from the set of subjects used in the

ticket promotion experiment the previous day. For most of the questions, we find little statistical differences in responses across test cells. However, we do find differences in responses to question 3 (iv) where we asked respondents to rate on an 11-point scale the extent to which they agree that a purchaser of a ticket in a given test condition "...wanted to feel good about yourself by donating to the charity." Figure 7 plots the purchase behavior in each of our experimental cells. For those cells with survey respondents, we also plot the corresponding mean self-reported warm glow level. Consistent with our theory, we see the warm glow changing very little across discount conditions when donation levels are low. But, large discounts reduce the warm glow a lot when donations are relatively high. The decline in warm glow is significant. The mean *warm glow* rating falling from 8.84 (5 RMB donation, 20 RMB discount) to 5.41 (10 RMB donation, 60 RMB discount). The F-stat between these two cells is 49.3, so we easily reject the null of equal means.[12] 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.

We also asked subjects to rate the statement "the discount was big enough to make it worthwhile for your to buy a movie ticket." Figure 8 shows that self-reported price sensitivity increases with the size of the discount. However, consistent with our signaling theory, the magnitude of the ratings and the magnitude of the increase in ratings as the discount increases is smaller for higher donation levels. That is, higher donations weaken the role of discounts on purchase behavior.

We can also test contextual inference about the quality of the movie. Subjects were asked to rate the statement "You wanted to watch the movie ..." on an 11-point scale. Unlike the self-reported warm-glow and price-sensitivity levels, the movie preference in Figure 9 is flat across price conditions with an average response of 8.76. Although, the mean rating does fall slightly as the charitable donation increases. The mean rating falls from 10.1 (5 RMB donation, 20 RMB discount) to 8.4 (15 RMB donation, 20 RMB discount), with an F-stat of 24.89. A limitation of this question is that it might simply reflect the mean movie taste, V, for inframarginal consumers as opposed to the mean perception of the movie quality. We construct an analogous test for contextual inference about the charity. Subjects were asked to rate the statement: "You valued the charity and wanted to support it" on an 11-point scale. Figure 10 shows the same flat pattern across promotional conditions, with an average rating of 9.28.

The survey also indicates that the subjects considered the charity itself to be legitimate and worthy. Over 80 percent of respondents gave a respone of at least 8 out of 11, and all of the responses were above 5. The results also indicate that subjects took the survey itself seriously and deliberated over their responses. In contrast with the rating of the charity, when asked "Will you continue donating money to this charity in the future?" the average score was 7.99, with only

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

44% of subjects giving scores of 7 or less, with some as low as 1. Mean responses are reported in Figure 11. We are not sure how to interpret responses to the rating task for the statement "Does this SMS deal seem too good to be true for you?" All the responses were over 7 and there was almost no difference in responses across cells (mean ranged from 9.6 to 10.4). This evidence is consistent with subjects' not inferring a negative quality signal about the movie in response to a larger discount and/or donation combination. However, subjects did score the statement "Do you think this purchase is an impulse buy?" quite low, with a mean of less than 5 across all cells, including those with discounts of 50% or more off the regular price.

6.3 Structural Estimates

We now look at the structural estimates. Our three key models are 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. The probit and random coefficients probit models are straw men since we know a priori that neither can predict the non-monotonic effect of prices in the data. It is nevertheless interesting to note that the final row of Table 8 reports the asymptotic approximation of the posterior log-likelihood (also known as the Schwarz or Bayeisan Information Criterion) to compare the fit of these three specifications. The Bayesian Information criterior has a built-in penalty for the number of parameters. We can see this as the fit of the random coefficients probit is inferior to that of the standard probit, even though the latter has no heterogeneity. However, the fit of our model with self-signaling fits considerably better than both of these other specifications. In spite of requiring only two additional parameters, Λ, the model is able to fit the non-montonic moments in our data. We show this fit in Figure 12. In the first column of panels, we show 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 the corresponding predicted choice behavior from the random coefficients probit. In the third column, we show the corresponding predicted choice behavior from the random coefficients probit with self-signaling. In the last two rows, we see how the self-signaling model is able to fit the non-monotonic relationship between price and choice rates when the donation levels are relatively high.

The structural coefficient estimates, Θ, in the final column of Table 8 provide some substantive implications about prosocial behavior in our ticket-buying context. First, the main effect of donations, γ, is statistically and economically insignificant; although we cannot rule out that the consumer's marginal consumption benefit from a 1 RMB donation is as low as -45 or as high as 9. In contrast, the diagnostic utility, λ_γ, is significant and economically large. Taken at face value, the average consumer derives no consumption benefit from donations. but derives large diagnostic

benefits from the posterior self-perception of valuing charitable donations. This striking finding is at odds with the conventional wisdom about consumer response to cause marketing campaigns.

Consumers also exhibit statistically significant sensitivity to prices and, in the absence of donations, demand slopes downwards as one would expect. We detect significantly negative marginal diagnostic utility from an individual's posterior belief about her own price sensitivity, λ_α. While discounts increase consumption utility which increases demand, the posterior belief that one is "price sensitive" also appears to increase diagnostic utility. This is the opposite sign of what has normally been assumed in theoretical studies of signaling (e.g. Benabou and Tirole (2006)). However, past work typically envisions a social setting in which the individual does not wish to appear greedy. In contrast, we study a private setting in which the individual might derive personal satisfaction from the self-perception of thrift or skill at finding a good deal.

6.4 The non-fungibility of Promotional Money

The structural estimates also point towards an interesting non-fungibility of promotional funds. By revealed preference, we would expect a discount always to be preferred to an equal-sized donation since the consumer could always donate the discounted amount to charity. However, once we account for diagnostic utility, there may be promotional states under which an incremental donation might be more effective than an incremental discount of the same magnitude. We illustrate this point in Figure 13. Both discounts and donations can be counter-productive. In the first panel, we observe regions where discounts and donations, both of which influence the strength of the warm-glow feeling, can reduce demand. At the same time, we also see that both can potentially increase demand. In the second panel, we observe a similar pattern with total net (of donation) revenues rising and falling in the levels of prices and donations respectively. This non-fungibility of promotion money puts to question the effectiveness of a cause marekting campaign. If the firm's objective is to increase current profitability, lower donations seem to be more effective. However, Figure 14 shows that if the firm's objective is to maximize the expected donation from consumers, it would in fact benefit from raising the donation level. As a result, the effectiveness of this cause marketing campaign depends on whether the firm wants to generate incremental current profits versus high donations.

7 Conclusions

In a large-scale field experiment that tested different cause marketing campaigns, 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. We quantify the self-signaling both with an attitudinal survey and with a structural model fit to purchase data. At face value, our estimates imply that the average consumer derives utility from the self-perception of valuing charity and not from the actual act of charitable giving.

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

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

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A Derivation of Posterior Expectations

The derivation of the posterior beliefs follows from standard results for multivariate Normal random variables. In our discrete choice purchase setting, the information signal consists of an inequality on the conditional indirect utility of buying versus not buying. For a random variable, $x \sim N(\mu, \sigma)$, the posterior expectation about x given signal $x > B$ is

$$E(x|x > B) = \mu + \sigma \frac{\phi\left(\frac{B-\mu}{\sigma}\right)}{1 - \Phi\left(\frac{B-\mu}{\sigma}\right)} \tag{9}$$

and given signal $x < B$ is

$$E(x|x < B) = \mu - \sigma \frac{\phi\left(\frac{B-\mu}{\sigma}\right)}{\Phi\left(\frac{B-\mu}{\sigma}\right)}.$$

For a multivariate Normal random vector, $(x_1, ..., x_n) \sim N(\mu, \Sigma)$, the conditional distribution of x_n is

$$(x_n|x_1, ..., x_{n-1}) \sim N\left(\mu_n + \Sigma_{n,-n}\Sigma_{-n}^{-1}\begin{bmatrix} x_1 - \mu_1 \\ \vdots \\ x_{n-1} - \mu_{n-1} \end{bmatrix}, \Sigma_{11} - \Sigma'_{n,-n}\Sigma_{-n}^{-1}\Sigma_{n,-n}\right) \tag{10}$$

where $-n$ denotes the vector $(1 : n-1)$.

In our model defined in equation 1, the purchase signal $y = 1$ is

$$\gamma a + \alpha p > -[V + \Delta(a, p, \lambda)].$$

Using 9 and 10, we can derive an individual's conditional expectation of model parameters $\Theta = (\gamma, \alpha, V)$ conditional on action y. For instance, the conditional posterior beliefs about donation

sensitivity are as follows:

$$E(\gamma|y=1) = \bar{\gamma} + \sigma_\gamma \int\int \frac{\phi\left(\frac{-\frac{V+\alpha p+\Delta(a,p,\Lambda)}{a}-\bar{\gamma}}{\sigma_\gamma}\right)}{1-\Phi\left(\frac{-\frac{V+\alpha p+\Delta(a,p,\Lambda)}{a}-\bar{\gamma}}{\sigma_\gamma}\right)} f(\alpha,V)\, d\alpha dV \tag{11}$$

$$E(\gamma|y=0) = \bar{\gamma} - \sigma_\gamma \int\int \frac{\phi\left(\frac{-\frac{V+\alpha p+\Delta(a,p,\Lambda)}{a}-\bar{\gamma}}{\sigma_\gamma}\right)}{\Phi\left(\frac{-\frac{V+\alpha p+\Delta(a,p,\Lambda)}{a}-\bar{\gamma}}{\sigma_\gamma}\right)} f(\alpha,V)\, d\alpha dV$$

where $\Sigma_{\gamma,-\gamma} = \left(\sigma_{\gamma,\alpha}, \sigma_{\gamma,V}\right)'$, $\Sigma_{-\gamma} = \begin{bmatrix} \sigma_\alpha^2 & \sigma_{\alpha,V} \\ \sigma_{\alpha,V} & \sigma_V^2 \end{bmatrix}$ and $f(\alpha,V)$ is the marginal bivariate Normal density of (α,V) with mean $(\bar{\alpha},\bar{V})'$ and covariance matrix $\Sigma_{-\gamma}$. The conditional beliefs $E(\alpha|y)$ are defined analogously. We compute the double-integrals in 11 using numerical Gauss-Hermite quadrature.

To simplify the notation, let $\delta_{\gamma 1} = E(\gamma|y=1), \delta_{\gamma 2} = E(\gamma|y=0)$, $\delta_{\alpha 1} = E(\alpha|y=1)$, $\delta_{\alpha 2} = E(\alpha|y=0)$, and $\delta = (\delta_{11}, \delta_{12}, \delta_{13}, \delta_{14})$. In addition, we can define the standardized normal random variables:

$$z_\gamma = \frac{-\frac{V+\alpha p+\left(\lambda_1\delta_{\gamma 1}+\lambda_2\delta_{\alpha 1}\right)-\left(\lambda_1\delta_{\gamma 2}+\lambda_2\delta_{\alpha 2}\right)}{a} - \bar{\gamma}}{\sigma_\gamma}$$

and

$$z_\alpha = \frac{-\frac{V+\gamma a+\left(\lambda_1\delta_{\gamma 1}+\lambda_2\delta_{\alpha 1}\right)-\left(\lambda_1\delta_{\gamma 2}+\lambda_2\delta_{\alpha 2}\right)}{p} - \bar{\alpha}}{\sigma_\alpha}.$$

We can re-write the system 11 above more compactly as

$$F\left(\bar{\Theta}, \Sigma_\Theta, \Lambda, a_t, p_t\right) \equiv \begin{bmatrix} \bar{\gamma} - \sigma_\gamma \int\int \varphi\left(z_\gamma;\alpha,V\right) f(\alpha,V)\, d\alpha dV \\ \bar{\gamma} + \sigma_\gamma \int\int \tilde{\varphi}\left(z_\gamma;\alpha,V\right) f(\alpha,V)\, d\alpha dV \\ \bar{\alpha} - \sigma_\alpha \int\int \varphi\left(z_\alpha;\gamma,V\right) f(\gamma,V)\, d\gamma dV \\ \bar{\alpha} + \sigma_\alpha \int\int \tilde{\varphi}\left(z_\alpha;\gamma,V\right) f(\gamma,V)\, d\gamma dV \end{bmatrix} = 0 \tag{12}$$

where $\varphi(z) = \frac{\phi(z)}{1-\Phi(z)}$ and $\tilde{\varphi}(z) = \frac{\phi(z)}{\Phi(z)}$ are the inverse Mills Ratios.

B Gradients of the MPEC Estimator

Recall that our MPEC estimator maximizes the objective function

$$log(\mathscr{L}) = \sum_t y_t log\left(\int \Phi\left(x_t'\left[\bar{\Theta}+\sigma' v\right]+\Delta(x_t,\Lambda)\right) f(v)\, dv\right) + \sum_t (1-y_t) log\left(\int \Phi\left(-x_t'\left[\bar{\Theta}+\sigma' v\right]-\Delta(x_t,\Lambda)\right) f(v)\, dv\right)$$

subject to the constraints

$$G(\delta) \equiv \left[\begin{array}{l} \delta_{\gamma 1} - \bar{\gamma} - \sigma_\gamma \int\int \varphi\left(z_\gamma V\right) f(\alpha, V)\, d\alpha dV \\ \delta_{\gamma 2} - \bar{\gamma} + \sigma_\gamma \int\int \tilde{\varphi}\left(z_\gamma\right) f(\alpha, V)\, d\alpha dV \\ \delta_{\alpha 1} - \bar{\alpha} - \sigma_\alpha \int\int \varphi\left(z_\alpha\right) f(\gamma, V)\, d\gamma dV \\ \delta_{\alpha 2} - \bar{\alpha} + \sigma_\alpha \int\int \tilde{\varphi}\left(z_\alpha\right) f(\gamma, V)\, d\gamma dV \end{array} \right] = 0$$

where $\varphi(z) = \frac{\phi(z)}{\Phi(-z)}$ and $\tilde{\varphi}(z) = \frac{\phi(z)}{\Phi(z)}$ are the inverse Mills ratios and

$$z_i = -\frac{x'_{-i}\left[\bar{\Theta}_{-i} + \sigma'_{-i}\nu_{-i}\right] + \Delta(x, \Lambda)}{x_i \sigma_i} - \frac{\bar{\Theta}_i}{\sigma_i},\ i \in \{\gamma, \alpha\}.$$

In the equations above, ν is a vector of standard Normal random variables and ϕ and Φ are the density and cdf respectively for the standard Normal distribution.

The gradients of the objective function are

$$\frac{\partial log(\mathscr{L})}{\partial \bar{\Theta}_k} = \sum_t y_t x_t \frac{\int \phi\left(x'_t\left[\bar{\Theta} + \sigma'\nu\right] + \Delta(x_t, \Lambda)\right) f(\nu)\, d\nu}{\int \Phi\left(x'_t\left[\bar{\Theta} + \sigma'\nu\right] + \Delta(x_t, \Lambda)\right) f(\nu)\, d\nu} - \sum_t (1 - y_t) x_t \frac{\int \phi\left(-x'_t\left[\bar{\Theta} + \sigma'\nu\right] - \Delta(x_t, \Lambda)\right) f(\nu)\, d\nu}{\int \Phi\left(-x'_t\left[\bar{\Theta} + \sigma'\nu\right] - \Delta(x_t, \Lambda)\right) f(\nu)\, d\nu}$$

$$\frac{\partial log(\mathscr{L})}{\partial \sigma_k} = \sum_t y_t x_t \frac{\int \phi\left(x'_t\left[\bar{\Theta} + \sigma'\nu\right] + \Delta(x_t, \Lambda)\right) \nu_k f(\nu)\, d\nu}{\int \Phi\left(x'_t\left[\bar{\Theta} + \sigma'\nu\right] + \Delta(x_t, \Lambda)\right) f(\nu)\, d\nu} - \sum_t (1 - y_t) x_t \frac{\int \phi\left(-x'_t\left[\bar{\Theta} + \sigma'\nu\right] - \Delta(x_t, \Lambda)\right) \nu_k f(\nu)\, d\nu}{\int \Phi\left(-x'_t\left[\bar{\Theta} + \sigma'\nu\right] - \Delta(x_t, \Lambda)\right) f(\nu)\, d\nu}$$

$$\frac{\partial log(\mathscr{L})}{\partial \lambda_i} = \sum_t y_t (\delta_{i1} - \delta_{i2}) \frac{\int \phi\left(x'_t\left[\bar{\Theta} + \sigma'\nu\right] + \Delta(x_t, \Lambda)\right) \nu_k f(\nu)\, d\nu}{\int \Phi\left(x'_t\left[\bar{\Theta} + \sigma'\nu\right] + \Delta(x_t, \Lambda)\right) f(\nu)\, d\nu} - \sum_t (1 - y_t)(\delta_{i1} - \delta_{i2}) \frac{\int \phi\left(-x'_t\left[\bar{\Theta} + \sigma'\nu\right] - \Delta(x_t, \Lambda)\right) \nu_k f(\nu)\, d\nu}{\int \Phi\left(-x'_t\left[\bar{\Theta} + \sigma'\nu\right] - \Delta(x_t, \Lambda)\right) f(\nu)\, d\nu}$$

$$\frac{\partial log(\mathscr{L})}{\partial \delta_{ij}} = \sum_t y_t \lambda_i \left(1 - 2\mathbb{I}_{\{y=j\}}\right) \frac{\int \phi\left(x'_t\left[\bar{\Theta} + \sigma'\nu\right] + \Delta(x_t, \Lambda)\right) \nu_k f(\nu)\, d\nu}{\int \Phi\left(x'_t\left[\bar{\Theta} + \sigma'\nu\right] + \Delta(x_t, \Lambda)\right) f(\nu)\, d\nu} - \sum_t (1 - y_t) \lambda_i \left(1 - 2\mathbb{I}_{\{y=j\}}\right) \frac{\int \phi\left(-x'_t\left[\bar{\Theta} + \sigma'\nu\right] - \Delta(x_t, \Lambda)\right) \nu_k f(\nu)\, d\nu}{\int \Phi\left(-x'_t\left[\bar{\Theta} + \sigma'\nu\right] - \Delta(x_t, \Lambda)\right) f(\nu)\, d\nu}.$$

The gradients for the constraints are

$$\frac{\partial G_{ij}(\delta)}{\partial \bar{\Theta}_k} = \begin{cases} -1 + \int\int \varphi'(z_i) f(\Theta_{-i})\, d\Theta_{-i}, & i = k, j = 1 \\ \frac{x_k}{x_i} \int\int \varphi'(z_i) f(\Theta_{-i})\, d\Theta_{-i}, & i \neq k, j = 1 \\ -1 - \int\int \tilde{\varphi}'(z_i) f(\Theta_{-i})\, d\Theta_{-i}, & i = k, j = 2 \\ -\frac{x_k}{x_i} \int\int \tilde{\varphi}'(z_i) f(\Theta_{-i})\, d\Theta_{-i}, & i \neq k, j = 2 \end{cases}$$

$$\frac{\partial G_{ij}(\delta)}{\partial \sigma_k} = \begin{cases} -\int\int \varphi(z_i) f(\Theta_{-i})\, d\Theta_{-i} + \int\int z_i \varphi'(z_i) f(\Theta_{-i})\, d\Theta_{-i}, & i = k, j = 1 \\ \frac{x_k}{x_i} \int\int \varphi'(z_i) \nu_k f(\nu)\, d\nu, & i \neq k, j = 1 \\ \int\int \tilde{\varphi}(z_i) f(\Theta_{-i})\, d\Theta_{-i} - \int\int z_i \tilde{\varphi}'(z_i) f(\Theta_{-i})\, d\Theta_{-i}, & i = k, j = 2 \\ -\frac{x_k}{x_i} \int\int \tilde{\varphi}'(z_i) \nu F(\nu)\, d\nu, & i \neq k, j = 2 \end{cases}$$

$$\frac{\partial G_{ij}(\delta)}{\partial \lambda_k} = \begin{cases} \frac{(\delta_{k1}-\delta_{k2})}{x_i}\int\int \varphi'(z_i) f(\Theta_{-i})\, d\Theta_{-i}, & i=k, j=1 \\ \frac{(\delta_{k1}-\delta_{k2})}{x_i}\int\int \varphi'(z_i) f(\Theta_{-i})\, d\Theta_{-i}, & i\neq k, j=1 \\ -\frac{(\delta_{k1}-\delta_{k2})}{x_i}\int\int \tilde{\varphi}'(z_i) f(\Theta_{-i})\, d\Theta_{-i}, & i=k, j=2 \\ -\frac{(\delta_{k1}-\delta_{k2})}{x_i}\int\int \tilde{\varphi}'(z_i) f(\Theta_{-i})\, d\Theta_{-i}, & i\neq k, j=2 \end{cases}$$

$$\frac{\partial G_{ij}(\delta)}{\partial \delta_{kl}} = \begin{cases} 1+\int\int \frac{\lambda_i}{x_i}\varphi'(z_i) f(\Theta_{-i})\, d\Theta_{-i}, & i=k, j=l=1 \\ 1+\int\int \frac{\lambda_i}{x_i}\tilde{\varphi}'(z_i) f(\Theta_{-i})\, d\Theta_{-i}, & i=k, j=l=2 \\ \int\int \frac{\lambda_k}{x_i}\varphi'(z_i) f(\Theta_{-i})\, d\Theta_{-i}, & i\neq k, j=l=1 \\ \int\int \frac{\lambda_k}{x_i}\tilde{\varphi}'(z_i) f(\Theta_{-i})\, d\Theta_{-i}, & i\neq k, j=l=2 \\ -\int\int \frac{\lambda_i}{x_i}\varphi'(z_i) f(\Theta_{-i})\, d\Theta_{-i}, & i=k, j=1, l=2 \\ -\int\int \frac{\lambda_i}{x_i}\tilde{\varphi}'(z_i) f(\Theta_{-i})\, d\Theta_{-i}, & i=k, j=2, l=1 \\ -\int\int \frac{\lambda_k}{x_i}\varphi'(z_i) f(\Theta_{-i})\, d\Theta_{-i}, & i\neq k, j=1, l=2 \\ -\int\int \frac{\lambda_k}{x_i}\tilde{\varphi}'(z_i) f(\Theta_{-i})\, d\Theta_{-i}, & i\neq k, j=2, l=1 \end{cases}$$

where $i \in \{\gamma, \alpha\}$ and $j = 1,2$ and $k \in \{\gamma, \alpha, V\}$ and $\varphi'(z) = \varphi(z)[-z+\varphi(z)]$ and $\tilde{\varphi}'(z) = -\tilde{\varphi}(z)[z+\tilde{\varphi}(z)]$.

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

Table 1: Experimental Design and Sample Size for Study 1

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

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

Table 2: Experimental Design and Sample Size for Study 2

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

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

Table 3: Summary Statistics

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

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

Table 4: Survey Response Rate

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

Table 5: Experimental Results

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

** Significant at the 1 percent level

* Significant at the 5 percent level

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

Table 6: Experimental Results

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

** Significant at the 1 percent level

* Significant at the 5 percent level



问卷设计(Survey Design) for NOT purchased customers

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

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

2、您觉得****的手机支付业务是否方便？

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

3、

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

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

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

(1)是因为想看电影，有没有折扣和捐赠，都会购买。

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

(2)是因为折扣很大很划算。

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

(3)是因为看重和支持本次捐助活动。

They valued the charity and wanted to support it.

(4)是因为向贫困老人捐钱后，他们对自己的感觉较好。

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

4、您认为，这些用户以后是否会继续参与"看电影做公益"活动，捐更多的钱？

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

5、您觉得，这些用户是否相信本次捐赠活动是真实可信的呢？

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

6、您觉得，这些用户是否认为他们就有责任去关心贫困孤独老人？

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

7、您觉得，这些用户是否觉得自己是个有爱心的人？

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

8、您觉得，这些用户本次购买是否是冲动购物？

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

Figure 1: Survey Questions for non-purchasers

	$a = 0.5$	$a = 0.5$
	$p = 7 - \mathbf{4.5} = 2.5$	$p = 7 - \mathbf{5} = 2$
$Pr(y = 1)$	0.0433	0.0353
$E(\gamma \mid y = 1)$	1.7258	1.5572
$E(\gamma \mid y = 0)$	0.6653	0.5773
$E(\alpha \mid y = 1)$	-0.1505	-0.2141
$E(\alpha \mid y = 0)$	-1.241	-1.4032
$\Delta(a, p, \Lambda)$	0.6393	0.6089

Table 7: Crowding out in the simluation

问卷设计(Survey Design) for purchased customers

1、您好，这里是****，可以耽误你一分钟的时间，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 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 consumers made the purchase in order to improve our business and customer service:

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

(1) 您本次购买，是因为想看电影，有没有折扣和捐赠，都会购买。

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

(2)您本次购买，是因为折扣很大很划算。

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

(3)您本次购买，是因为您看重和支持本次捐助活动。

The consumer values the charity and wanted to support it.

1

(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?

Figure 2: Survey Questions for purchasers

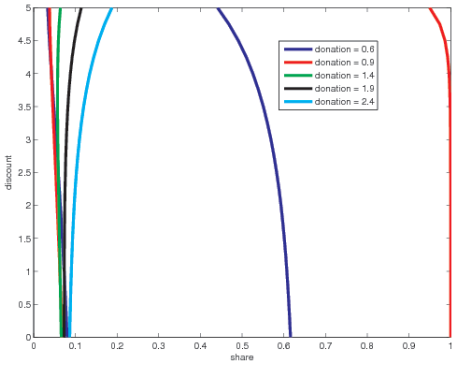


Figure 3: Equilibrium Choice Rules and Multiplicity

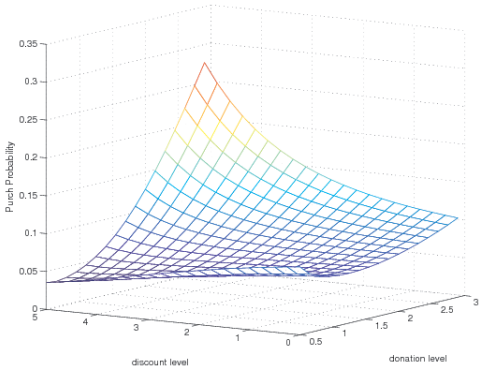


Figure 4: Purchase probability for the simulation

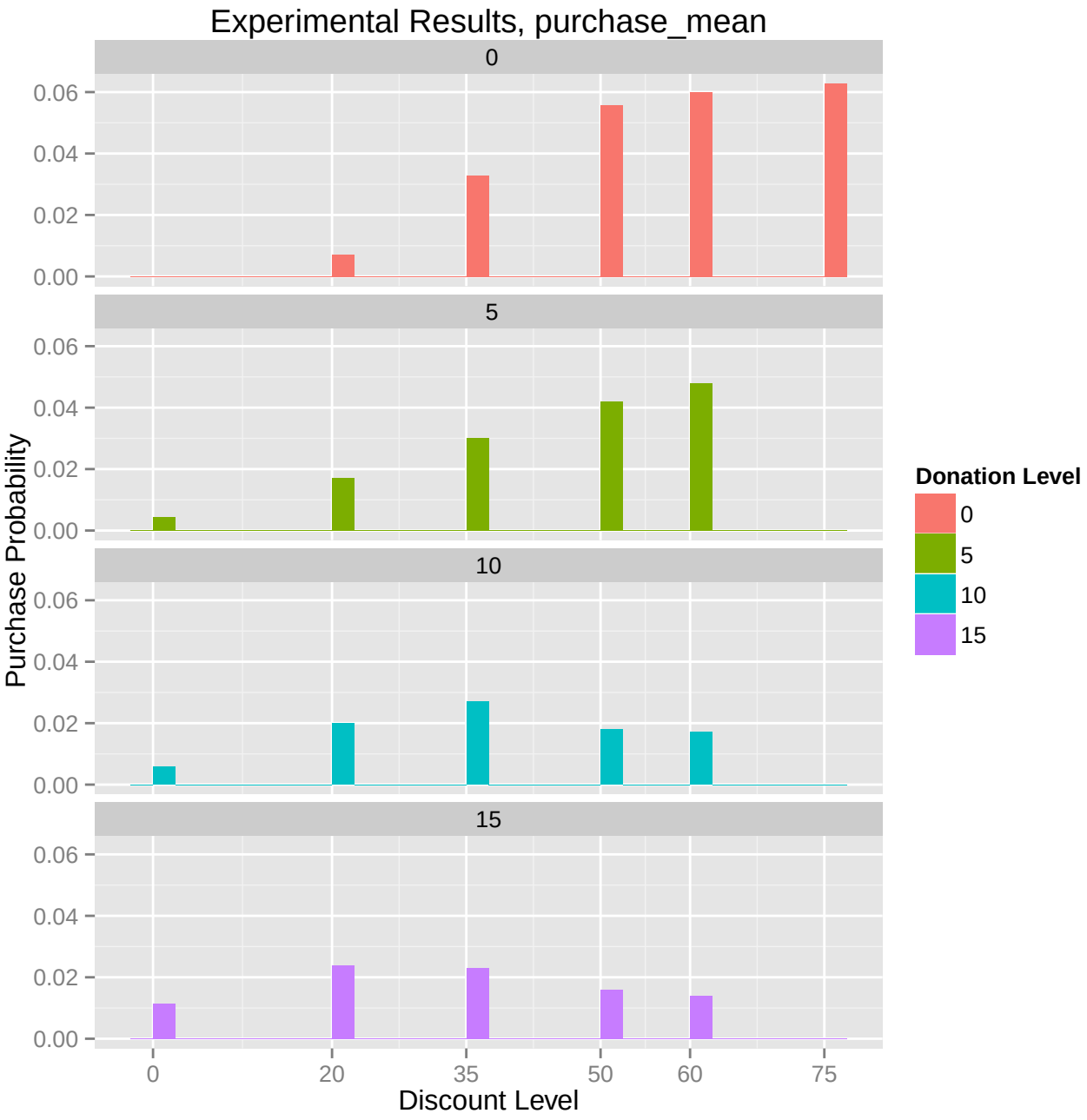


Figure 5: Purchase rate by promotional condition

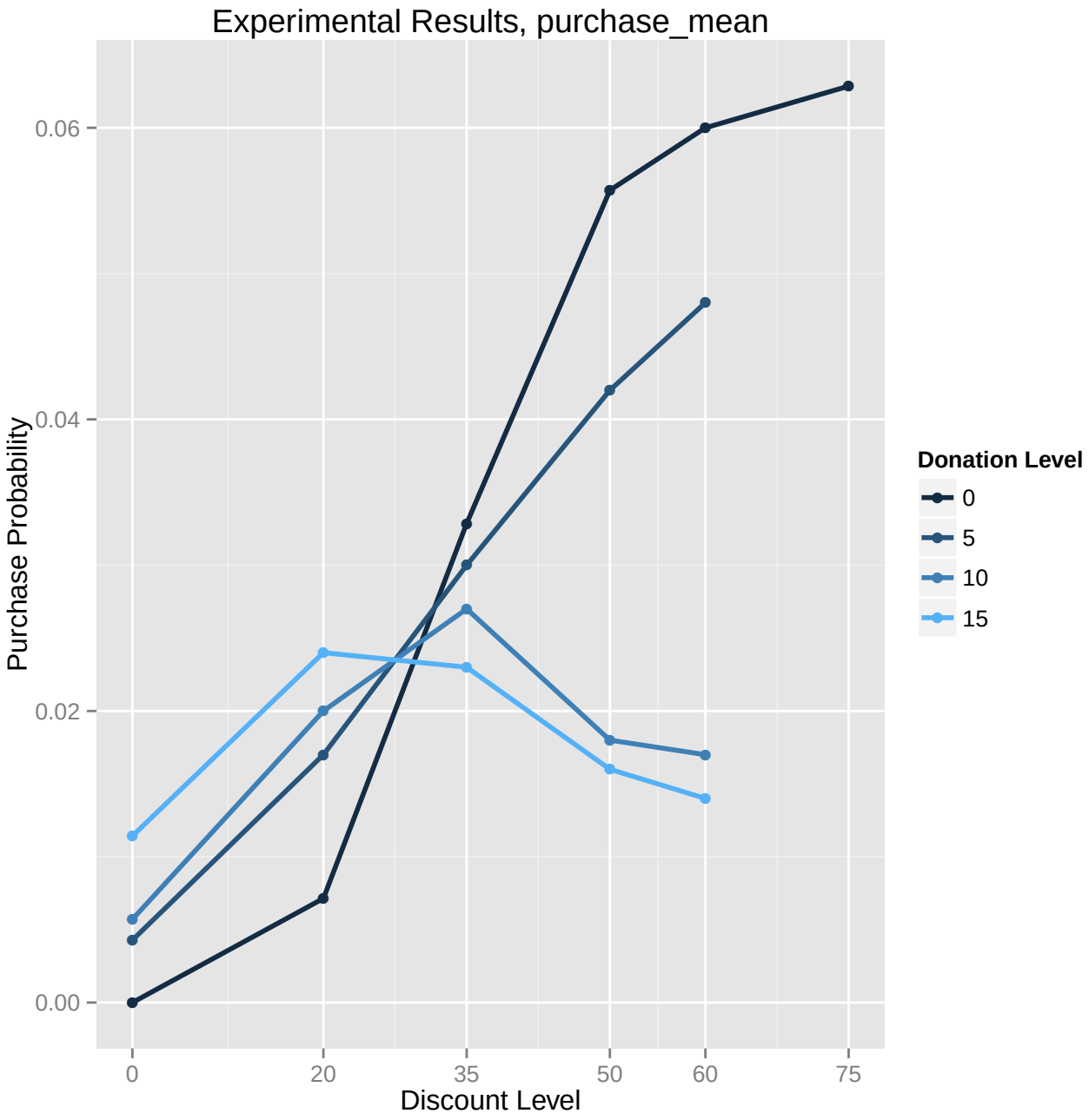


Figure 6: Purchase rate by promotional condition

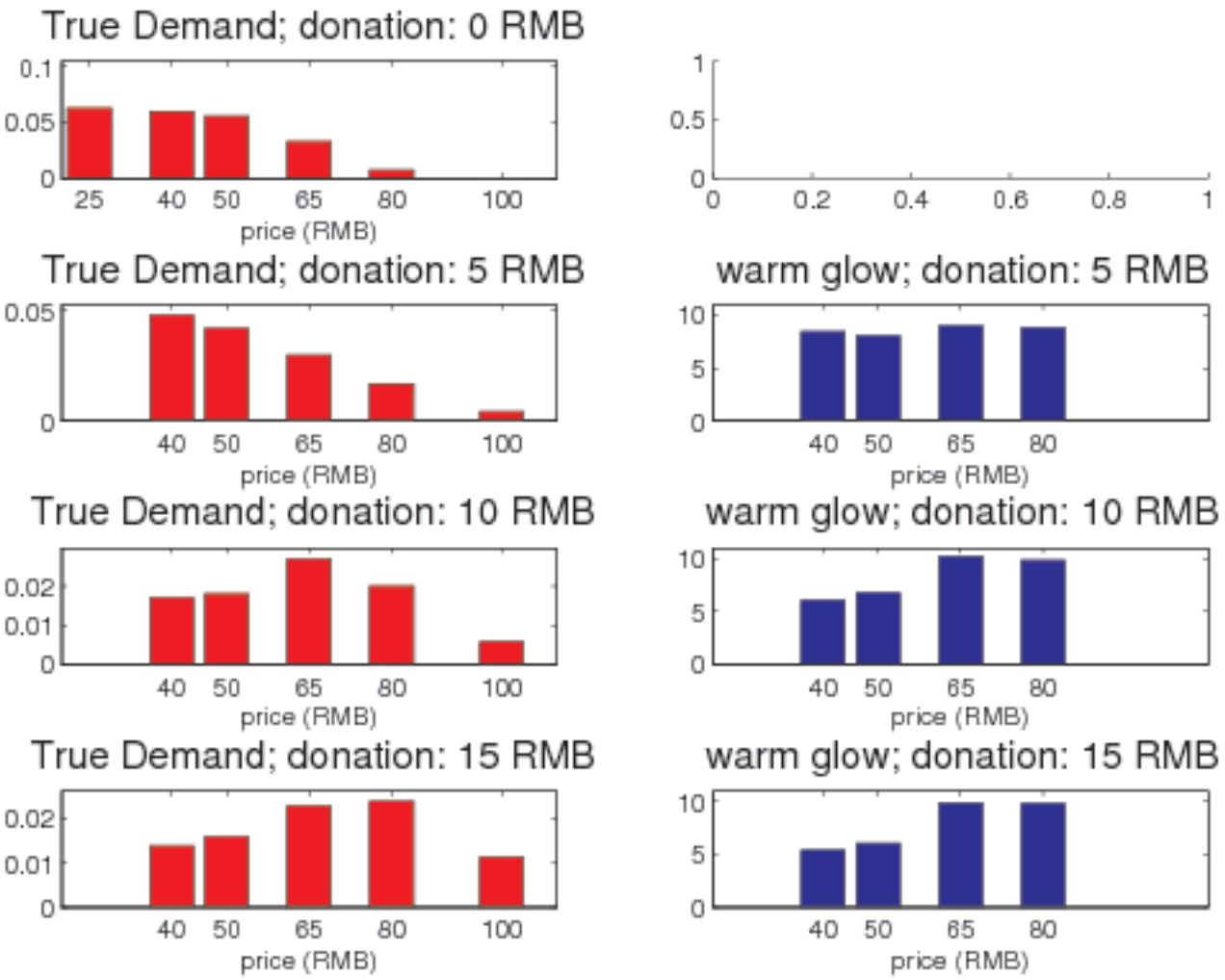


Figure 7: Survey: Warm Glow Feeling

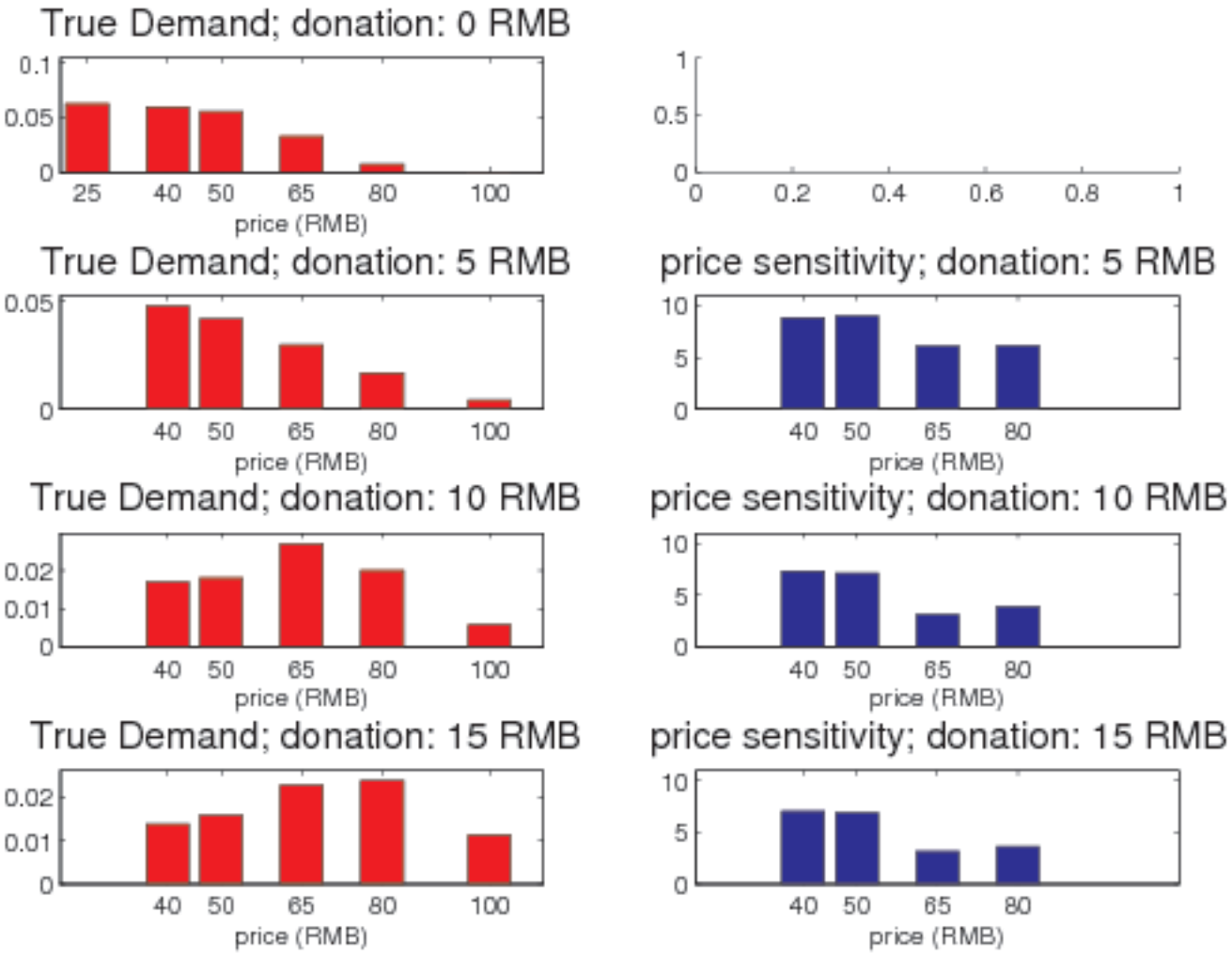


Figure 8: Survey: Price Sensitivity

	Probit		*R.C. Probit*		*Self-Signaling*	
	coefficient	*st. error*	*coefficient*	*st. error*	*coefficient*	*st. error*
Donation, $\bar{\gamma}$	-0.022	0.0005	-0.0414	0.0111	*-0.1411*	*0.1345*
Price, $\bar{\alpha}$	-0.0063	0.0001	-0.0068	0.0047	*-0.0183*	*0.0077*
Intercept, $\bar{V}$	-1.4373	0.0099	-1.3741	0.1474	*-0.8526*	*0.225*
σ_γ			0.0360	0.0104	*0.1327*	*0.0632*
σ_α			0.0000	2246.7162	*0.0001*	*0.307*
λ_γ					*2.1948*	*0.7931*
λ_α					*-15.9831*	*3.452*
$\mathscr{L}$	-3254.0865		-3251.9625		-3215.9887	
BIC	6539.1297		6555.5195		6504.2097	

Table 8: Structural Estimates and Model Fits

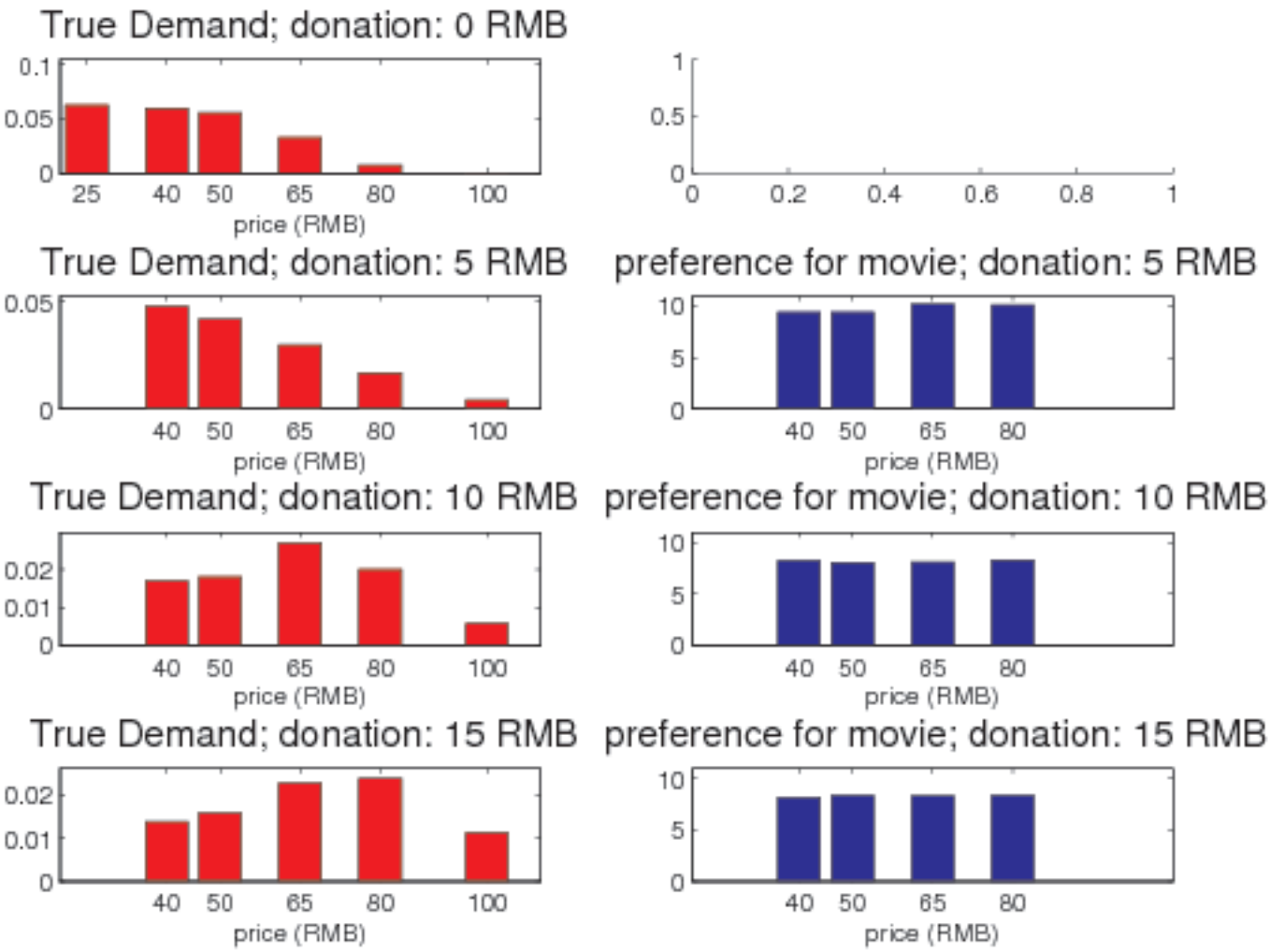


Figure 9: Survey: want to see the movie

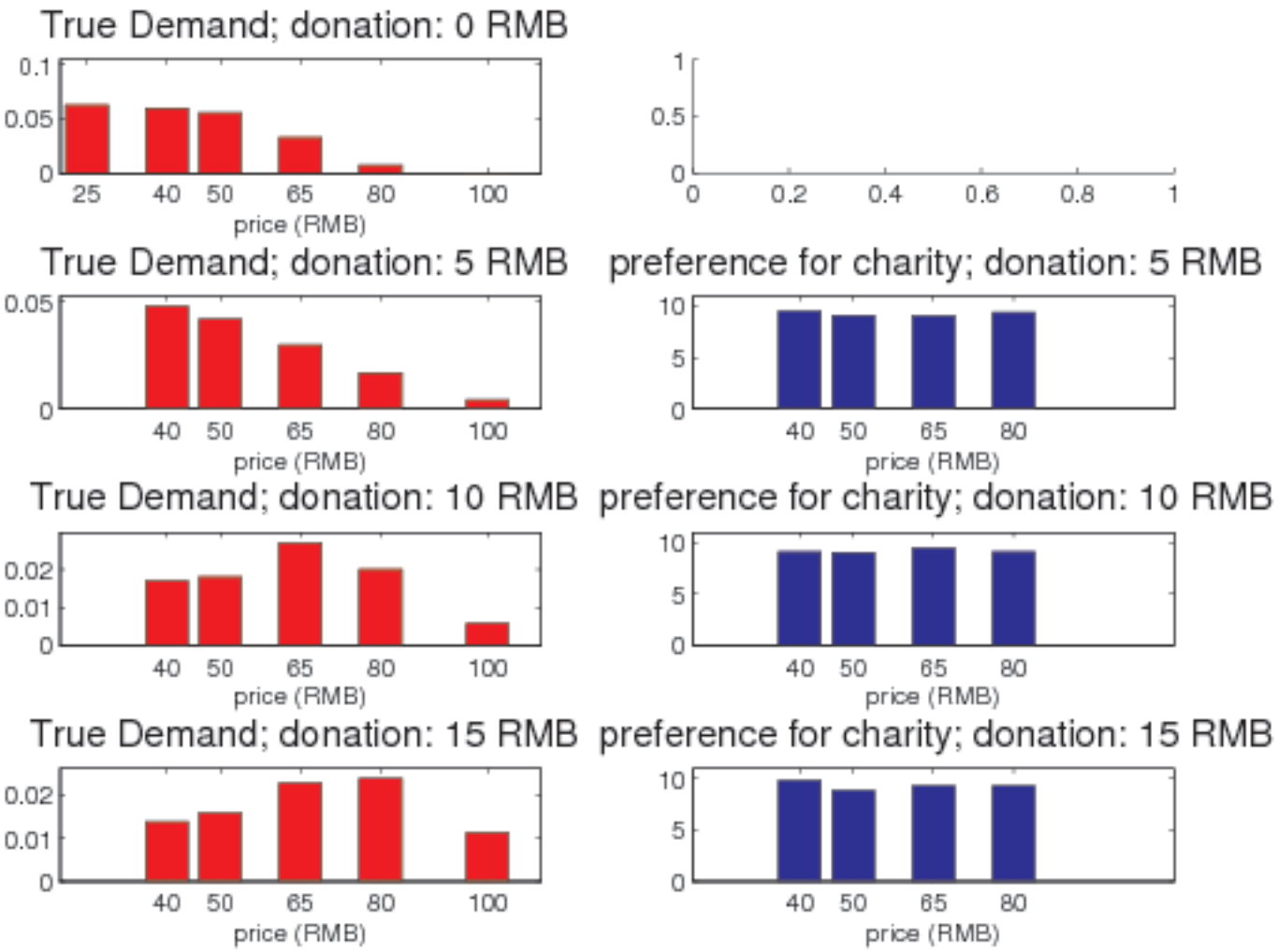


Figure 10: Survey: Value the Charity itself

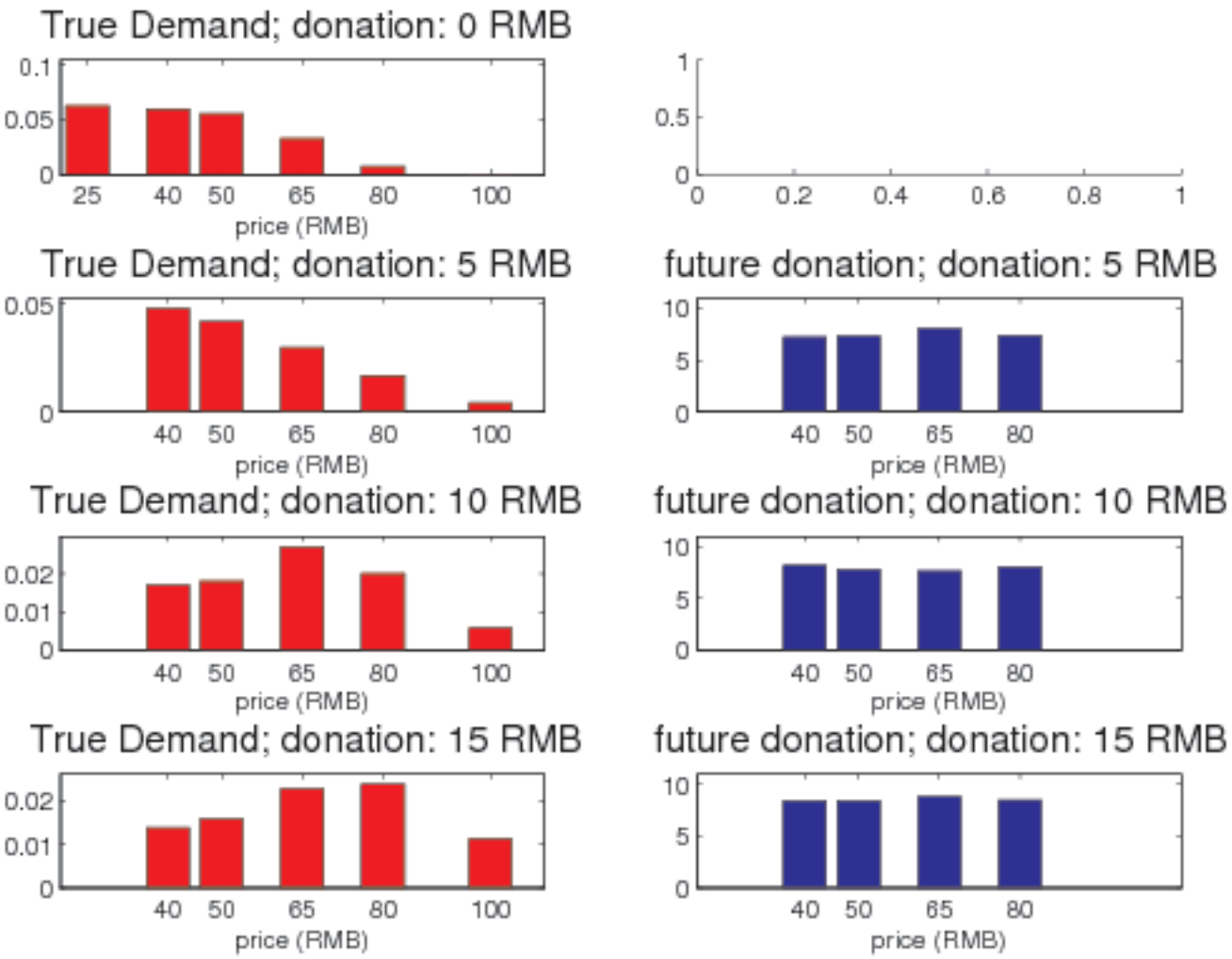


Figure 11: Survey: Intend to donate to charity in future

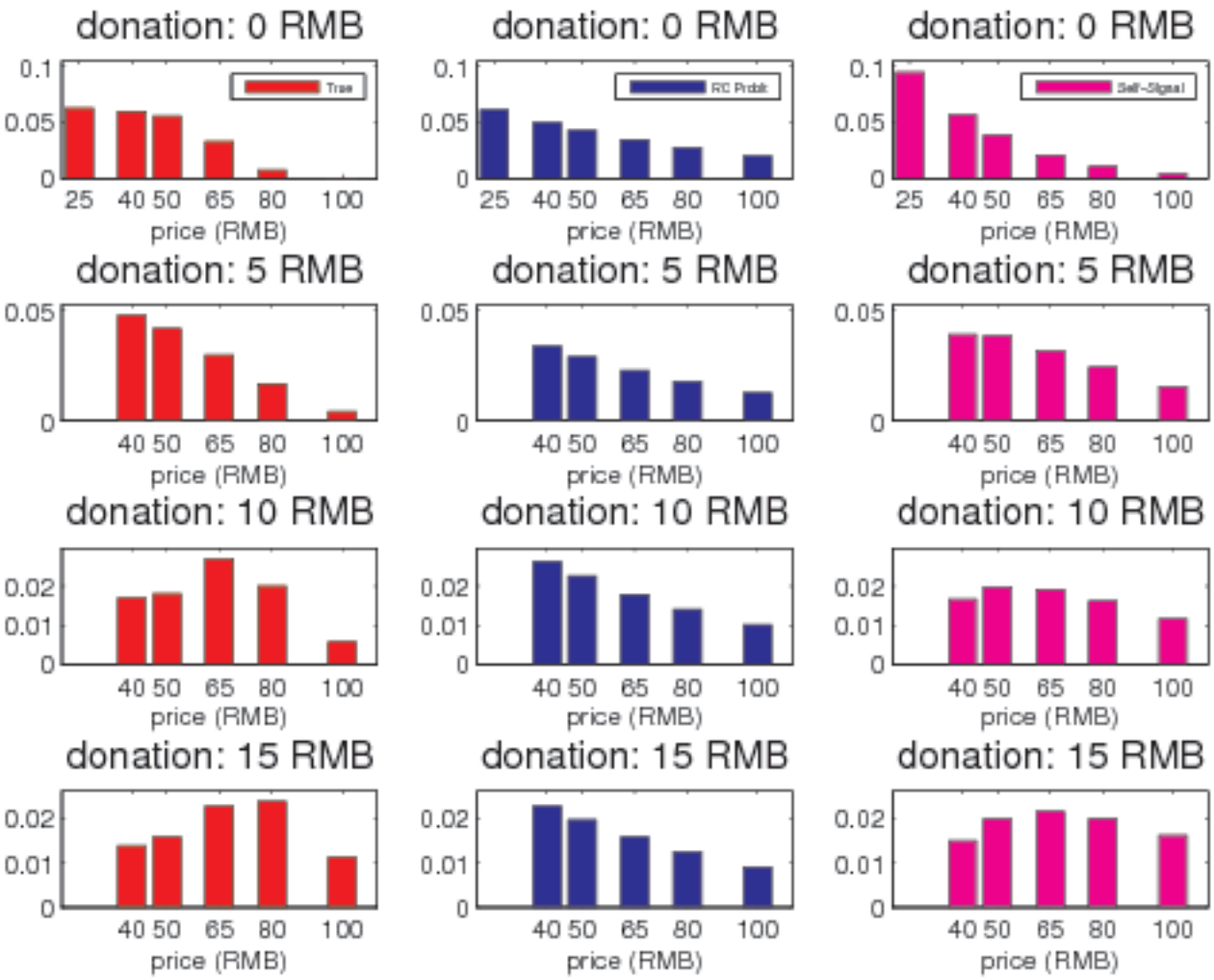


Figure 12: In-Sample Fit of the Stuctural Models

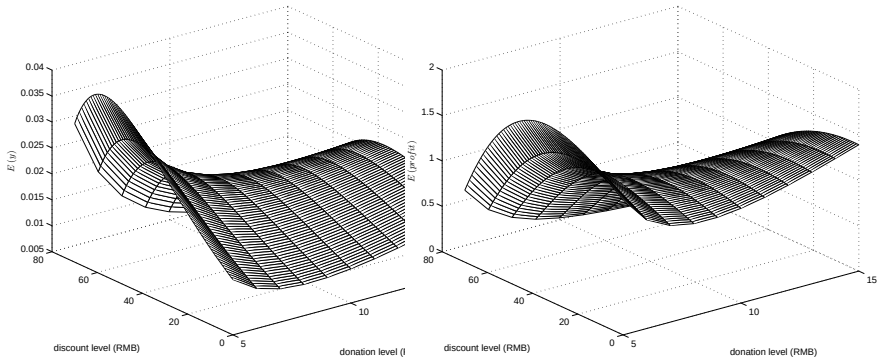


Figure 13: Predicted purchase rates and net revenues under different promotional campaigns

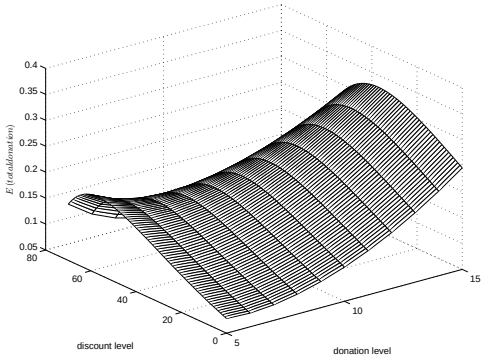


Figure 14: Predicted donations under different promotional campaigns