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Abstract

Survey data are often subject to a number of biases. In this article several models are proposed to detect and adjust for survey response bias. The approach is then applied to the analysis of a market survey data on the demand for an advanced electronic device in a developing country. Substantial differences in take rates and price elasticities are found between the estimates derived from the conventional random utility maximization framework and the biased response model. © 1999 Elsevier Science S.A. All rights reserved.

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1. Introduction

Sample survey is widely used by marketing researchers. However, both sample errors and nonsample errors could occur. While one may view sample errors as the unavoidable cost of using a segment of the population to project the characteristics of the whole population, the nonsample errors could adversely affect the validity of the inference. Since non-sample errors are typically

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attributed to poorly designed survey instruments; vague, inconsistent or misleading administration procedures; and respondent reactions to the research process itself, etc. (e.g. Hufnagel and Conca, 1994), traditional focus of controlling response bias is through better control of factors that tend to bias the outcome (e.g. Brackstone et al., 1975; Cannell and Oksenberg, 1986; Deming, 1944; Lansing et al., 1961; Lessler, 1984; Madow, 1965; Sing and Chaudhary, 1986; Sudman and Bradburn, 1974; Thompson, 1992).

However, there are large areas of opinion preferences and actions where no matter how hard survey researchers attempted, respondents still would not like to reveal the truth. There are also cases where investigators have no control of sample design, nor do they possess independent sample of accurately measured response to cross validate the existence of response bias. If systematic response bias exists in the sample, models based on the assumption that respondents reveal the truth are likely to spread misinformation. It is then of critical importance to detect whether or not any systematic response bias is present, and if they do, how to adjust the inference to avoid the possibility of 'garbage in' and 'garbage out'. In this paper we propose a statistical approach to detect and adjust for response bias as a complement to the traditional sample design improvement techniques and double sampling methods. We focus our investigation on the case of qualitative choice models. For the analysis of continuous data with exaggerated response, e.g. see Klein and Sherman (1997).

In Section 2, we propose various response models. We then apply the methodology to analyze an actual survey data with regard to the demand for an advanced electronic device in a developing country in Section 3. Conclusions are in Section 4. Appendix A demonstrates the identifiability of the proposed models. Appendix B provides a description of the data.

2. The models

In this section we propose various survey response models for analyzing the categorical data. For simplicity, we assume that a survey respondent is confronted with a set of mutually exclusive and collectively exhaustive alternatives, $C = \{0, 1, \ldots, M\}$. The results can be easily modified to incorporate the case that each respondent, n, is confronted with a different choice set, C_n.

The basic framework of the qualitative response model we shall follow is the conventional random utility model (e.g. McFadden, 1974). Let U_{jn} be the (indirect) utility associated with the jth alternative for the nth respondent. We assume that U_{jn} can be decomposed into two components,

$$U_{jn} = \mu_{jn} + \xi_{jn}, \quad j = 0, \ldots, M, \tag{2.1}$$

where μ_{jn} is a nonstochastic function of personal and mode specific attributes $\underset{\sim}{x}_{jn}$ and ξ_{jn} represent the effects of all other factors, assumed to possess the properties of a random variable. Let

$$y_{jn}^{*} = \begin{cases} 1 & \text{if } U_{jn} = \max(U_{0n}, \ldots, U_{Mn}), \\ 0 & \text{otherwise.} \end{cases} \tag{2.2}$$

Then $P(y_{jn}^{*} = 1) = F_j(\mu_{0n}, \mu_{1n}, \ldots, \mu_{Mn}) = F_{jn}$, where F_j is a distribution function derived from the density function of ξ_{jn}. For instance, if ξ_{jn} is independently, identically distributed across j and n with Type I extreme-value density function (Johnson and Kotz, 1970),[1] then we have the conditional logit model (e.g. Lerman, 1977; Maddala, 1983; McFadden, 1974, 1984; Train, 1986),

$$P(y_{jn}^{*} = 1) = \frac{e^{\mu_{jn}}}{\sum_{l=0}^{M} e^{\mu_{ln}}} = \frac{e^{\mu_{jn} - \mu_{0n}}}{1 + \sum_{l=1}^{M} e^{\mu_{ln} - \mu_{0n}}} = F_{jn}, \qquad j = 0, 1, \ldots, M$$
$$\text{and} \quad n = 1, \ldots, N. \tag{2.3}$$

Let the observed variable y_{jn} be defined as

$$y_{jn} = \begin{cases} 1 & \text{if the } j\text{th alternative is chosen by the } n\text{th respondent,} \\ 0 & \text{otherwise.} \end{cases}$$

The first model we consider corresponds to the case that the respondent truly reveals his/her preference. That is, $y_{jn} = y_{jn}^{*}$, and

$$P(y_{jn} = 1) = P(y_{jn}^{*} = 1) = F_{jn}.$$

We shall call this the *random utility model.*

In addition to the standard random utility model based on the assumption that a respondent tells the truth, we also wish to consider models that take account of the systematic distortion on the part of respondent. It is well known that a respondent may not reveal the truth because he/she (1) does not understand the nature of his/her own preferences; (2) wants to impress the interviewer; (3) is trying to guess what the right answer is (e.g., what the sponsor or interviewer would prefer him/her to say); or (4) simply misunderstands the question (Andersen, 1988, Chapter 9). In this paper we propose two models to detect deliberate response bias. One of the response bias model notes that

[1] Of course, if we wish, we can let ξ_{jn} be other distribution, say multivariate normal, then we will have a multivariate probit model for $P(y_{jn}^{*} = 1)$.

sometimes the respondents do not have enough knowledge about the survey question and will skew their answers in either directions. For instance, when asked some information of a behavior happened very long time ago or confronted with a new product, respondents usually do not have memory or knowledge and state an impromptu answer rather than admitting ignorance. They may act in favor of providing information by guessing or by choosing an answer randomly in order to avoid the embarrassment of not having an answer for the question. To model such randomized response, we assume that there is a probability π_{jn} that the nth individual will choose the jth alternative for $j = 0, 1, \ldots, M$, irrespective of his underlying preference, where π_{jn} could be a function of some socio-demographic variables $\underset{\sim}{z}_n$. We assume that $\sum_{j=0}^{M} \pi_{jn} < 1$. Let $\pi_n^* = 1 - \sum_{j=0}^{M} \pi_{jn}$, then with probability $\pi_n^* > 0$ a respondent will tell the truth. Therefore, the probability of observing the nth individual choosing the jth alternative is given by

$$P(y_{jn} = 1) = \pi_{jn} + \left(1 - \sum_{j=0}^{M} \pi_{jn}\right) F_{jn} = \pi_{jn} + \pi_n^* F_{jn}, \quad j = 0, \ldots, M. \tag{2.6}$$

We shall call this second model the *randomized response model.*

The other response bias model focuses on the situation where the systematic bias arises from the respondents wanting to impress the interviewer or to guess what the sponsor or interviewer would prefer him/her to say. Situations like this may arise because of the existence of the natural ordering of the alternatives. For instance, there could be 'social desirability biases' (Bagozzi, 1994), namely, the 'tendency for an individual to present him or herself ... in a way that makes the person look positive with regard to culturally desired norms and standards' (Ganster et al., 1983, p. 322). Thus, when responding to nominal categories, people may in different degrees over-report 'desirable' ones and under-report 'undesirable' ones. For instance, because of certain educational ideas in the society, it may appear more impressive to be a reader of the New York Times than of the Daily News. Consequently, the respondents may overstate their reading of the New York Times and understate their reading of the Daily News when asked 'Which paper do you usually read?' Similarly there could be 'answer order bias', namely, the tendency for respondents, other things equal, to give higher ratings to alternatives higher on a list than those lower on a list (Andersen, 1988, Chapter 9). It is also well known that when respondents are asked about future demand of a new product or service, they often exaggerate their demands and present positive response bias (e.g. Klein and Sherman, 1997). To model the possibility of respondents wanting to impress the interviewer and biasing the choices in certain directions, we assume that there exists a natural ordering of the alternatives and takes no action as indicated by 0 as a base. We introduce an indicator w_{jn} with probability π_{jn} that $w_{jn} = 1$ and probability

$(1 - \pi_{jn})$ that $w_{jn} = 0$. An individual will choose the jth alternative if either $y^*_{jn} = 1$ or the indicator $w_{jn} = 1$ and $w_{j'n} = 0$ for $j' > j$ according to some ranking of the alternatives. Then

$$\mathrm{P}(y_{jn} = 1) = \mathrm{Prob}[(y^*_{jn} = 1 \quad \text{and} \quad w_{j'n} = 0 \text{ for } j' \geqslant j)$$

or

$$(w_{jn} = 1 \quad \text{and} \quad y^*_{j'n} = 0 \text{ for } j' > j)] \quad = \left[1 - \sum_{i=j}^{M} \pi_{in}\right] F_{jn} + \pi_{jn}\left[\sum_{i=0}^{j} F_{jn}\right],$$

$$\text{for} \quad = 1, \ldots, M, \tag{2.7}$$

and

$$\mathrm{P}(y_{0n} = 1) = 1 - \sum_{j=1}^{M} \mathrm{P}(y_{jn} = 1).$$

We shall call this third model the *one-sided response bias model.*

The difference between models 2 and 3 is that in the former model a respondent's choice to certain alternatives can be biased in either direction while in the latter model the bias is one-sided. The one-sided bias response model is useful in cases where the alternatives have a natural ranking of certain sort. For instance, in measuring one's preference for certain product, the question can be intensively preferred, moderately preferred, indifferent, moderately dislike, or intensively dislike. Or in measuring the potential use of certain product, the classification can be heavy user, moderate user, or not a user, etc. In these situations, the response bias could be one-sided in the sense that only respondents whose true preferences are j' could have positive chances to choose the alternative j for $j > j'$, but there is no chance that an individual with preference j' will choose i where $i < j'$. In other words, when there is a natural ordering in the alternatives by certain criteria, there is a positive probability of observing exaggerated response. It can be easily seen that under the assumption of this model $\mathrm{P}(y_{Mn} = 1) > \mathrm{P}(y^*_{Mn} = 1)$ and $\mathrm{P}(y_{0n} = 1) < \mathrm{P}(y^*_{0n} = 1)$. However, for $0 < j < M$, whether the observed probability $\mathrm{P}(y_{jn} = 1)$ is greater or less than $\mathrm{P}(y^*_{jn} = 1)$ depends on whether $\pi_{jn}(\sum_{i=0}^{j} F_{in})$ is greater or less than $(\sum_{i=j}^{M} \pi_{in})F_{jn}$. On the other hand, in the randomized response model a respondent's choice will reflect his true preference only with probability $(1 - \sum_{i=0}^{M} \pi_{in})$ and there is a probability π_{jn} that he will choose the jth alternative no matter what his underlying preference is. Whether $\mathrm{P}(y_{jn} = 1)$ is greater or less than $\mathrm{P}(y^*_{jn} = 1)$ depends on whether $(\pi_{jn}/(1 - \pi^*_n))$ is greater or less than F_{jn}. In the case of binary choice, the two models are identical.

To the best of our knowledge, we do not know any formulation similar to the one-sided response bias model. However, the randomized response model is of

the same form as the latent trait model in psychology (e.g. Birnbaum, 1968; Bock, 1972; Samejima, 1969) or the randomized design model proposed by Warner (1965) (also see Ljungqvist, 1993; Maddala and Trost, 1978). However, the motivations are different. The Birnbaum's model is developed to study test scores with various general or special abilities or attitudes. In the case of randomized sample design, the motivation is to conceal from the interviewer the exact meaning of the respondent's answer so that the respondent is more likely to answer sensitive questions truthfully. The motivation for formulating a randomized response model is to detect possible bias when an investigator is confronted with a data set which may be contaminated. Furthermore, the π_{jn} in a randomized design is known to researchers while the π_{jn} in latent trait model or our randomized response model is unknown to the investigator and needs to be estimated.

These three types of behavioral response models are fairly general in the sense that the response bias probabilities can be the same across individuals or can be functions of individual socio-demographic variables, $\underset{\sim}{z}_n$. The only restrictions are that $0 \leqslant \pi_{jn} < 1$ and $\sum_{j=0}^{N} \pi_{jn} < 1$. The condition that $\sum_{j=0}^{M} \pi_{jn} < 1$ is crucial for uncovering the true preference. A simple way to impose the restriction that $0 \leqslant \pi_{jn} < 1$ without much computational difficulty is to let $\pi_{jn} = G_j(\underset{\sim}{\gamma}_j' \underset{\sim}{z}_n)$, where $G_j(\cdot)$ be a probability distribution function is usually sufficient to meet all the prior restrictions for the one-sided response bias model because as Eq. (2.7) indicated, the maximum sum of π_{jn} is $\sum_{j=1}^{M} G_j(\underset{\sim}{\gamma}_j' \underset{\sim}{z}_n)$, which except for extreme cases, will be less than 1. However, the condition that G_j be a probability distribution function will not be sufficient to ensure that $\sum_{j=0}^{M} \pi_{jn} < 1$. In fact, if G_j is a probability distribution function, then $\sum_{j=0}^{M} G_j(\cdot) = 1$. Therefore, for model 2, instead of simply defining $\pi_{jn} = G_j(\underset{\sim}{\gamma}_j' \underset{\sim}{z}_n)$, we let $\pi_{jn} = \Phi(\underset{\sim}{a}' \underset{\sim}{z}_n) G_j(\underset{\sim}{\gamma}_j' \underset{\sim}{z}_n)$, where Φ is another probability distribution, say, an integrated normal distribution function. Then, in general,

$$\sum_{j=0}^{M} \pi_{jn} = \Phi(\underset{\sim}{a}' \underset{\sim}{z}_n)\left[\sum_{j=0}^{M} G_j(\underset{\sim}{\gamma}_j' \underset{\sim}{z}_n)\right] = \Phi(\underset{\sim}{a}' \underset{\sim}{z}_n) < 1.$$

With a parametric specification of π_{jn} and F_{jn}, all three models are identified under fairly general conditions (See Appendix A).[2] Therefore, all three models

[2] It is hard to formulate a biased response model from a nonparametric approach. The nonparametric approach typically starts by estimating the conditional mean of y_{jn} given the attributes. The formulation does not appear to allow the separation of π_{jn} from F_{jn}. In other words, the gain of generality by not parametrically specifying the probability distribution of ξ_{jn} is counterweighed by having to assume the response reflects true preference.

can be estimated by maximizing the log-likelihood function

$$\log L = \sum_{n=1}^{N} \sum_{j=0}^{M} y_{jn} \log \mathrm{P}(y_{jn} = 1), \tag{2.8}$$

with $\mathrm{P}(y_{jn} = 1)$ defined according to Eqs. (2.5) and (2.6) or Eq. (2.7), respectively. Under fairly general conditions, the maximum likelihood estimator is consistent and asymptotically normally distributed with the asymptotic covariance matrix equal to the inverse of the negative of the information matrix (Sun, 1995).

The true data generating process is unknown to researchers. However, model 1 is nested within models 2 and 3. Under our formulation of π_{jn} being specified as a probability distribution function of the arguments of $\underset{\sim}{a}'\underset{\sim}{z}_n$ or $\underset{\sim}{\gamma}_j'\underset{\sim}{z}_n$, the parameter space will have to be unbounded to make $\pi_{jn} \to 0$. This will result in singularity of the MLE for models 2 and 3. Hence, if we start from the formulation of models 2 and 3 and find singularity in obtaining the MLE, this is an indication that the true data generating process may not be subject to response bias. To double check on this conjecture we simplify respecify $\pi_{jn} = \pi_j$ with $0 \leqslant \pi_j < 1$ for all n. Because the MLE is consistent and asymptotically normally distributed, it is expected that maximizing the likelihood function of model 2 or 3 will yield consistent estimators with the estimates of π_j approaching to 0 if the data were generated from model 1. Therefore, conventional t-test can be used to distinguish model 1 from model 2 or 3. On the other hand, models 2 and 3 are nonnested. If the data were generated from model 2 and we maximize the likelihood function based on model 3 or vice versa, the resulting estimators will be biased. To select the best approximation, often one relies on certain model selection criteria. The six conventionally used model selection criteria for quantal data as summarized by Amemiya (1981) are: percentage of correct prediction (CP), sum of squared residuals (SSR), Efron's (1973) R^2 (RSQ), squared correlation coefficient (SCC), and Akaike (1973) information criteria (AIC). In addition, we can also use prediction performance of each model as a criterion. Splitting up the sample into two parts, using the first part to estimate each of the three models, then using the estimated model to predict the outcomes of the second part of observations, the model that has the best prediction performance is chosen.

The results of Monte Carlo experiments suggest that (Hsiao and Sun, 1997): First, there is hardly any information loss if one estimates model 2 or 3 even the data are generated from model 1. Second, if the data are generated from model 2 or 3 but if one estimates the wrong model (model 1 and model 3 or 2), the estimates are severely biased. Third, AIC and prediction criteria appear very reliable in selecting the best approximating model. Thus, if there is a possibility that the data may be contaminated by response bias, it is advisable not to start

with the conventional random utility model 1. Instead, one should begin with models 2 and 3 as preliminary data exploration window. Then use AIC to select the best approximating model.

3. An application to the analysis of demand for an advanced electronic device

In this section we apply the methodology to analyze the demand for an advanced electronic device in a developing country based on a market survey conducted in late 1993 where the product is yet to be introduced.[3] The sample of this study is generated from exogenous stratified sample. There are 1024 respondents with 262 from socioeconomic group A, 280 from group B, and 482 from group C. Groups A, B and C are top income categories in the country. They consist of 6%, 12% and 28% of the population, respectively.

The survey was carefully designed to collect socio-demographic variables of the respondents such as age, marital status, education, occupation, wealth, sex, etc. as well as their preference ordering for the service of the electronic device. However, information on household income was not collected. The choice set contains four mutually exclusive choices – Frequent User plan (denoted by 3), Moderate User Plan (2), Infrequent User Plan (1) and Non-User Plan (0). There were 50 price scenarios that include a one time installation fee and monthly fees for the three different user plans. Only one price scenario was quoted to any given respondent. Each respondent was then asked to choose one of the three service plans or none of them. Further description of this data is provided in Appendix B.

Our basic contention for model specification is that the demand for this electronic device is a function of the price, income, and perceived need of the service. The price variables used are the installation charge and monthly usage fee. The income variable is not available. We approximate it by the home ownership dummy and the socioeconomic group dummy variables or the interaction of the socioeconomic group dummy variables and the choice-specific constant dummy variables. The perceived need is approximated by the choice-specific dummy, socio demographic variables such as age, sex, martial status, occupation and current user of computer, beeper, etc. We follow the Hendry (1993) general-to-specific progressive modeling strategy. The criteria we use to obtain a simple structure are that the included variables have

[3] Because of the proprietary concern, we are not able to provide the detail of this data set.

signs consistent with a priori structure, reasonable t-statistics and improve prediction.[4]

Both the ordered probit and logit forms are chosen for the choice probability F_{jn}. For the ordered probit model, we assume that $y_{0n}^* = 1$ if $\mu_n + \xi_n < 0$, $y_{1n}^* = 1$ if $0 < \mu_n + \xi_n < D_1$, $y_{2n}^* = 1$ if $D_1 < \mu_n + \xi_n < D_2$ and $y_{3n}^* = 1$ if $D_2 < \mu_n + \xi_n$. For the logit model, we assume that $y_{jn}^* = 1$ if $U_{jn} = \max(U_{0n}, U_{1n}, U_{2n}, U_{3n})$ as in Eqs. (2.2) and (2.3). The specification of μ_{jn} involves own price but does not involve cross-price term because only factors affecting the relative odds ratio appear in Eq. (2.3). However, the cross-price term does appear in the specification of $P(y_{jn}^* = 1)$ because $(\mu_{jn} - \mu_{0n})$ for all j appears in the denominator. The simultaneity issue between the choice of this electronic device and other electronic devices are avoided because the product has yet to be introduced into the country. The current usage of computer or beeper is mainly used as proxies for perceived need or unobserved individual preference. Maximum likelihood methods are used to estimate all these models. The detail of the model specification and the estimates based on random utility model that $P(y_{jn}^* = 1) = P(y_{jn} = 1)$ are provided in Table 1 for the logit model and the first column of Table 4 for the ordered probit model. All the price coefficients of the logit model have the correct signs. But the price coefficient of user fee for the infrequent user plan for the ordered probit model has the wrong sign.

The random utility model is estimated based on the assumption that respondents truly indicate their preference. However, two-thirds of the responses indicate they would choose one or the other usage plan while in the same time the penetration rate of this product for the developed countries like U.S. or Canada is about 5%. The proportion of positive response of this sample does appear abnormally high. Given that respondents enthusiastic about a product often exaggerated their demands, we also estimate the randomized response and one-sided response bias models with the assumption that $\pi_{jn} = \pi_j$. Since the unconstrained estimates of π_3 and π_2 (or π_0) for both the one-sided or randomized response models are very close to zero, we impose the restrictions that π_3, and π_2 or π_0 are equal to zero. Tables 2 and 3 provide the revised estimates of $P(y_{jn}^* = 1)$ and π_1 of the randomized and one-sided response bias models for

[4] In fact, our preferred model is the one without choice specific constants. In this model, the price coefficients for $pm - h$, $pm - m$ and $pm - \ell$ are -0.03, -0.005, and -0.025 with t-values -6.59, -2.13 and -2.47 for model 1, -0.03, -0.005, -0.05 with t-values, -6.54, -2.22 and -1.47 for model 2 and -0.03, -0.008, -0.05 with t-values -6.76, -2.7 and -2 for model 3. The percent of correct predictions and AIC values are 0.4885 and 216.63 for model 1, 0.4891 and 215.83 for model 2, 0.4937 and 215.03 for model 3. However, in the paper we report the results based on the inclusion of choice-specific constants to avoid possible misleading inference that the identification of the randomized response or one-sided response bias model is due to the omission of these constants, at the expense of somewhat less significant t-statistics, perhaps due to multicollinearity.

Table 1
Logit estimates of demand for an advanced electronic device by model 1 (random utility model)

	Description of variables	Frequent	Moderate	Infrequent
	Constant term of High user plan	−1.751 (0.72)		
c-m	Constant term of Moderate user plan		0.356 (0.73)	
c-l	Constant term of Infrequent user plan			−0.104 (0.20)
	Monthly fee for Frequent user plan	−0.017 (0.86)		
pm-m	Monthly fee for Moderate user plan		−0.011 (1.46)	
	Monthly fee for Infrequent user plan			−0.033 (1.77)
	Age-under 35	0.593 (1.87)		
beeper	Current user of beeper		0.322 (1.72)	
	Education-technico Complete/university incomplete		0.324 (1.78)	
	Education-university complete		0.246 (1.43)	
house	Own house	0.697 (1.64)		0.406 (1.81)
	Executive of large company	1.164 (2.59)		
	Retired, unemployed and other		−0.695 (3.02)	−0.471 (2.56)
pc	Current user of pc	1.181 (3.62)	0.413 (2.81)	
sex	Male		−0.222 (1.72)	

Number of observations is 980.

the logit specification and Table 4, columns 2 and 3 for the ordered probit specification.

There is not much difference of the estimated β for $P(y_{2n}^* = 1)$ and $P(y_{3n}^* = 1)$, but the differences of the estimated β for $P(y_{1n}^* = 1)$ are much more pronounced for these three type of models, presumably because π_3 and π_2 (or π_0) are restricted to be zero but $\pi_1 \neq 0$. In general, the estimated price coefficients in absolute values are the largest for the one-sided response model, the smallest for the random utility model, with the randomized response model in the middle. With a logit specification of the latent preference the point estimates of π_1 are

Table 2
Logit estimates of demand for an advanced electronic device by Model 2 (randomized response model)

	Description of variables	Frequent	Moderate	Infrequent
c-h	Constant term of	− 1.621		

Table 4
Ordered Probit Estimates of demand for an advanced electronic device

	Description of variables	Random Utility	Two-sided	One-sided
c	Constant term	1.443	1.451	1.473
		(2.37)	(2.27)	(2.38)
pm-h	Monthly fee for	− 0.69e-2	− 0.129e-2	− 0.695e-2
	Frequent user plan	(1.44)	(1.43)	(1.55)
pm-m	Monthly fee for	− 0.86e-3	− 0.89e-2	− 0.889e-2
	Moderate user plan	(1.93)	(1.81)	(1.97)
	Monthly fee for	0.65e-2	0.74e-2	0.701e-2
	Infrequent user plan	(0.72)	(0.77)	(0.77)
age1	Age-under 35	0.276	0.288	0.261
		(3.52)	(3.10)	(3.31)
beeper	Current user of beeper	− 0.101	− 0.096	0.085
		(0.89)	(0.80)	(0.73)
	Education-technico	0.143	0.145	0.197
	Complete/university incomplete	(1.43)	(1.35)	(1.96)
	Education-university complete	0.087	0.091	0.125
		(0.91)	(0.89)	(1.32)
house	Own house	0.169	0.190	0.141
		(1.55)	(1.61)	(1.26)
occ1	Executive of large company	0.316	0.387	0.372
		(2.39)	(2.25)	(2.40)
occ9	Retired, unemployed and other	− 0.340	− 0.356	− 0.502
		(3.51)	(2.92)	(3.72)
pc	Current user of pc	0.234	0.289	0.285
		(3.37)	(3.05)	(3.48)
sex	Male	0.057	0.060	0.143
		(0.76)	(0.76)	(1.93)
D1	Threshold 1	0.687	0.540	0.692
		(17.64)	(2.38)	(4.35)
D2	Threshold 2	1.556	1.607	1.557
		(20.50)	(8.35)	(20.85)
π_1	Percentage of respondents		0.067	0.055
	Randomly taking		(0.69)	(1.84)
	Infrequent user plan			

Number of observations is 980. All the model selection criterion are calculated by using 789 observations.

his/her true preference is the non-user plan for the one-sided response model and 6.7% for the randomized response model.

Because the implication of different model specification is quite different, it is essential that we choose a best approximation. Since the estimated π_1 is statistically highly significant, presumably we can reject the hypothesis that the responses truly reflect the underlying preferences. However, from the estimated

Table 5
Prediction comparison of three models*: logit and ordered probit specifications

	Random utility model		Randomized response model		One-sided response model	
	Logit	Probit	Logit	Probit	Logit	Probit
CP	0.48503	0.45561	0.48853	0.46032	0.49102	0.46599
RSQ	0.052021	0.051546	0.052299	0.052311	0.058805	0.053608
SCC	0.053864	0.051541	0.053664	0.052257	0.057264	0.054144
AIC**	216.609	217.457	216.033	217.163	215.474	216.052

*All the model prediction criterion are calculated by using 289 observations.

t-values, it is hard to distinguish a logit specification from an ordered probit specification or within the logit specification to distinguish the randomized response model from the one-sided response model. From a 'theory consistent' perspective, a logit specification for the latent preference is preferable to an ordered probit specification because the ordered probit model has the wrong sign for the price variable. Model selection statistics also favor the logit model. Table 5 provides the statistics of various model selection criteria. It would appear that a one-sided response bias model with a logit specification for the latent preference is a preferred specification based on the AIC criterion.

The above analysis is based on the assumption that the error terms follow certain parametric distribution. Ideally, one would like to use a more general distributional assumption of the error terms or a distribution-free method (e.g. Stern, 1996). However, although the parameter estimates may be sensitive to the distributional assumption, there is little empirical evidence that such methods yield more plausible or statistically significantly different predictions in the range of interest to the policy makers (e.g. Newey et al., 1990). In fact, with so many possibilities that exist, it is impossible to estimate the probability that an empirical model could have arisen from chance. As Griliches (1967) has noted that 'we may be asking too much of our data. We want them to test our theories, provide us with estimates of important parameters, and disclose to us the exact form of the interrelationships between the variables'. We believe that analyzing some simple structural models based on perhaps stringent assumptions one at a time can yield useful insights that often cannot be obtained from the approach of starting with a collection of numerical data and subjecting them to a purely data-based approach with most general assumption that encompasses all special models. Therefore, we shall take the approach that all models are simply approximations to the unknown true data generating process. The question then becomes whether the random utility model or either of the two response bias models is a better approximation to the data at hand and can pass what Friedman and Schwartz (1991) consider 'the real proof of (the) pudding is

Table 6
Comparison of take rates by the three models

Price-cell Sample	Frequent	Moderate	Infrequent	Sample take-rate	Population penetration
Interest	18.79	41.50	20.74	81.03	38.25
Demand	5.37	36.23	25.10	66.70	30.63
Random utility model					
1	4.90	34.30	27.01	66.22	30.35
2	5.15	47.90	10.85	63.90	29.26
3	5.28	37.03	21.12	63.44	29.05
4	5.09	31.86	28.02	64.97	29.77
5	5.31	33.23	24.88	63.42	29.05
6	5.51	34.50	21.98	61.98	29.38
7	5.28	29.51	28.99	63.78	29.24
8	5.51	30.83	25.77	62.11	28.61
Randomized response model					
1	5.29	38.09	18.73	62.32	28.52
2	5.57	51.12	4.86	61.55	28.16
3	5.90	40.87	12.79	59.56	27.24
4	5.73	35.51	19.52	60.76	27.80
5	5.97	36.97	16.21	59.16	27.06
6	6.17	38.23	13.36	57.77	26.41
7	5.97	33.02	20.28	59.26	27.13
8	6.22	34.43	16.87	57.53	26.63
One-sided response bias model					
1	4.92	31.46	14.65	51.02	23.33
2	5.06	42.47	2.24	49.78	22.75
3	5.30	33.78	8.40	47.48	21.69
4	5.69	29.13	15.14	49.37	22.57
5	5.32	30.38	11.56	47.25	21.59
6	5.50	31.36	8.71	45.58	20.81
7	5.26	26.91	15.63	47.79	21.88
8	5.50	28.10	11.94	45.54	20.73

whether it produces a satisfactory explanation of data not used in baking it – data for subsequent or earlier years, for other countries, or for other variables'. We examine this issue using two criteria: the prediction performance comparison and Vuong (1989) likelihood ratio test for model selection. To compare the predictive performance of the three models, we randomly split the sample into two parts. The first part consists of slightly more than two-thirds of the sample. The second part consists of the remaining 289 observations. We use the first part to estimate the three models. We then predict the outcome of the second part of the sample based on the estimated model. Table 6 provides the prediction comparison of different models. Again one-sided response bias model with

a logit specification for the latent preference dominates. The percentage of correct prediction is 0.49. This appears to be a fairly satisfactory performance for a cross-section data.

To test if the difference in prediction error is significant, we follow Vuong (1989) in assuming that the true data generating process is unknown and perform likelihood ratio tests for model selection. Since model 1 is nested within models 2 and 3, we shall simply rely on the t-statistics to test the null hypothesis that $\pi_j = 0$. However, between models 2 and 3, they are nonnested. So are the choices between logit and ordered probit. So we shall rely on the Vuong likelihood ratio statistic to see if two models approximating the true data generating process equally well or one is actually better than the other. The Vuong (1989) likelihood ratio statistic of model 3 against model 2 with a logit specification for the latent response is 4.978 and with an order-probit specification is 2.106. Both are statistically significant at 5% level. That is, the null hypothesis that models 2 and 3 approximate the true data generating process equally well is rejected in favor of model 3. The Vuong likelihood ratio statistic of model 3 between a logit and an ordered probit specification for the latent preference is 3.879, which again favors the logit formulation.

To conclude, all these model selection criteria suggest that one-sided response bias model with a logit specification of the latent preference is a better approximation to the true data generating process than the conventional random utility model for this data set. We may say that there is about 18.5% chance that an individual who is a non-user would select the infrequent user plan in his response. Since there are substantial differences in the estimated $\underset{\sim}{\beta}$ of $P(y_{1n}^* = 1)$ for these three models, it is interesting to compare the differences of their policy implications. We note that it is $P(y_{jn}^* = 1)$, not $P(y_{jn} = 1)$, that is of interest to policy makers. However, the discrete choice model focuses on individual behavior, while the policy maker is more interested in aggregate behavior. To obtain the market level of take rates or price elasticities, we need to aggregate the disaggregated model. For instance, the aggregate proportion of selecting the jth alternative is given by

$$\bar{P}(j) = \int P(y_j^* = 1 \mid \underset{\sim}{x}) f(\underset{\sim}{x})\, d\underset{\sim}{x},$$

where $P(y_j^* = 1 \mid x)$ denotes the latent (true) preference function, not the observed preference function, $P(y_j = 1 \mid x)$, $f(\underset{\sim}{x})$ denotes the population density of $\underset{\sim}{x}$.

Unfortunately, $f(\underset{\sim}{x})$ is unknown. If the sample were randomly drawn, $\bar{P}(j)$ can be approximated by

$$\hat{P}(j) = \frac{1}{N} \sum_{n=1}^{N} P(y_{jn}^* = 1 \mid \underset{\sim}{x}_n).$$

If N is large, $\hat{\bar{P}}(j)$ will be close to $\bar{P}(j)$. However, our sample is a stratified random sample. Therefore, to estimate $\bar{P}(j)$, we use the formula

$$\begin{aligned}\hat{\bar{P}}(j) = 0.06 \times \frac{1}{N_A} \sum_{n \in D_A} P(y_{jn}^* = 1 \mid \underset{\sim}{x}_{jn}, d_{An} = 1) + 0.12 \\ \times \frac{1}{N_B} \sum_{n \in D_B} P(y_{jn}^* = 1 \mid \underset{\sim}{x}_{jn}, d_{Bn} = 1) + 0.28 \\ \times \frac{1}{N_C} \sum_{n \in D_C} P(y_{jn}^* = 1 \mid \underset{\sim}{x}_{jn} d_{Cn} = 1),\end{aligned} \tag{3.3}$$

where

$$d_{gn} = \begin{cases} 1 & \text{if the observation comes from the } g\text{th socio} - \text{economic group,} \\ 0 & \text{otherwise,} \end{cases}$$

$D_{gn} = \{n \mid d_{gn} = 1\}$ denotes the set of individuals that come from the gth group, and N_g denotes the number of individuals in the gth group, for $g = \text{A, B or C}$.

Similarly, under the assumption that the value of some variable x_{jkn} for each individual is altered by some increment so that

$$\frac{dx_{jkn}}{x_{jkn}} = \frac{dx_{jkn'}}{x_{jkn'}} = \frac{dx_{jk}}{x_{jk}} \quad \text{for all } n \text{ and } n', \tag{3.4}$$

where $x_{jk} = (1/N)\sum_{n=1}^{N} x_{jnk}$, then the direct and cross elasticities can be approximated by

$$\begin{aligned} e_{jk} = \frac{\beta_j x_{jk}}{\hat{\bar{P}}}(j) \cdot \Big\{ 0.06 \cdot \frac{1}{N_A} \sum_{An \in D_A} P(y_{jn}^* = 1 \mid \underset{\sim}{x}_{jn}, d_{An} = 1) \\ \times [1 - P(y_{jn}^* = 1 \mid \underset{\sim}{x}_{jn}, d_{An} = 1)] + 0.12 \\ \times \frac{1}{N_B} \sum_{Bn \in D_B} P(y_{jn}^* = 1 \mid \underset{\sim}{x}_{jn}, d_{Bn} = 1)[1 - P(y_{jn}^* = 1 \mid \underset{\sim}{x}_{jn}, d_{Bn} = 1)] \\ + 0.28 \times \frac{1}{N_C} \sum_{Cn \in D_C} P(y_{jn}^* = 1 \mid \underset{\sim}{x}_{jn}, d_{Cn} = 1) \end{aligned} \tag{3.5}$$

and

$$\hat{e}_{lk} = -\frac{\beta_l x_{lk}}{\hat{P}(j)} \cdot \left\{ 0.06 \times \frac{1}{N_{An\in D_A}} \sum P(y_{jn}^* = 1 \mid \underset{\sim}{x}_{jn}, d_{An} = 1) \right.$$

$$\times P(y_{ln}^* = 1 \mid \underset{\sim}{x}_{ln}, d_{An} = 1) + 0.12 \times \frac{1}{N_{Bn\in D_B}} \sum P(y_{jn}^* = 1 \mid \underset{\sim}{x}_{jn}, d_{Bn} = 1)$$

$$\times P(y_{ln}^* = 1 \mid \underset{\sim}{x}_{ln}, d_{Bn} = 1) + 0.28 \times \frac{1}{N_{Cn\in D_C}} \sum P(y_{jn}^* = 1 \mid \underset{\sim}{x}_{jn}, d_{Cn} = 1)$$

$$\left. \times P(y_{ln}^* = 1 \mid \underset{\sim}{x}_{ln}, d_{Cn} = 1) \right\} \tag{3.6}$$

Tables 6 and 7 present the estimated market take rates and own- and cross-price elasticities for the three models with a logit specification for the latent preference. The estimated take rate for either of three user plans for the sample (using e.g. Eq. (3.2)) under the assumption of random utility model is about 66%. Under the assumption of one-sided response model this take rate is reduced to about only 45%. However, since the sample is a stratified random sample, we have to weigh the market take rate for each socio-economic group by their respective weights in the population. Hence, for the population as a whole, as shown in Table 6, the take rate for either of the three plans varies between 28.6% and 30.4%, 26.4% and 28.5%, and 20.7% and 23.3%, for the random utility, random response and one-sided response model, respectively.

There are also substantial differences in the estimated own price and cross-price elasticities. Table 7 shows that for the frequent user plan, the randomized response model exhibits the highest own-price elasticity, with the random utility model the next and the one-sided response bias model the smallest. For the moderate user plan, the one-sided response model has the highest own-price elasticity, the random utility model next, and the randomized response model the smallest. For the infrequent user plan, the one-sided response model has the largest own price elasticity, the randomized response model next, and the random utility model the smallest.

To summarize, under the assumption that a one-sided response bias is a better approximation to the true data generating process, the expected take rates for either of the three user plans range between 20% and 23%. The own-price elasticities for the frequent user plan, moderate user plan and infrequent user plan are of the order -1.7, -0.4, and -1.7, respectively. The cross-price elasticity of the frequent user and moderate user or infrequent user plan is of the order 0.2. The cross-price elasticity of the moderate user and frequent user or infrequent user plan is of the order of 0.09 and 0.18, respectively. The cross-price elasticity between infrequent user and frequent user or moderate user plan is of the order of 0.09 or 0.2, respectively.

Table 7
Direct and cross-price elasticity by three models

Frequent user plan

	Model 1			Model 2			Model 3		
Price-cell[a]	H-H[b]	M-H[c]	L-H	H-H	M-H	L-H	H-H	M-H	L-H
1	−1.721	0.200	0.171	−1.837	0.222	0.171	−1.717	0.180	0.194
2	−1.716	0.137	0.172	−1.834	0.147	0.113	−1.711	0.121	0.077
3	−1.711	0.215	0.201	−1.825	0.237	0.177	−1.706	0.193	0.169
4	−1.716	0.223	0.177	−1.830	0.249	0.178	−1.713	0.201	0.201
5	−1.710	0.232	0.197	−1.823	0.258	0.186	−1.706	0.209	0.193
6	−1.705	0.240	0.209	−1.817	0.267	0.185	−1.700	0.216	0.176
7	−1.715	0.259	0.198	−1.828	0.285	0.204	−1.713	0.234	0.237
8	−1.709	0.268	0.221	−1.820	0.295	0.216	−1.706	0.242	0.236

Moderate user plan

	Model 1			Model 2			Model 3		
Price-cell	H-M	M-M	L-M	H-M	M-M	L-M	H-M	M-M	L-M
1	0.091	−0.363	0.139	0.109	−0.343	0.169	0.090	−0.377	0.183
2	0.094	−0.143	0.173	0.109	−0.135	0.111	0.092	−0.158	0.072
3	0.098	−0.348	0.174	0.117	−0.328	0.174	0.097	−0.364	0.159
4	0.095	−0.452	0.203	0.114	−0.429	0.176	0.093	−0.469	0.190
5	0.099	−0.443	0.199	0.119	−0.419	0.183	0.097	−0.460	0.182
6	0.102	−0.434	0.211	0.123	−0.411	0.182	0.101	−0.453	0.166
7	0.099	−0.547	0.186	0.119	−0.522	0.183	0.096	−0.566	0.196
8	0.097	−0.125	0.199	0.120	−0.120	0.185	0.099	−0.127	0.197

Infrequent user plan

	Model 1			Model 2			Model 3		
Price-cell	H-L	M-L	L-L	H-L	M-L	L-L	H-L	M-L	L-L
1	0.085	0.188	−0.471	0.105	0.210	−0.731	0.091	0.173	−1.060
2	0.090	0.132	−1.446	0.109	0.143	−2.180	0.097	0.119	−3.122
3	0.092	0.203	−0.765	0.114	0.227	−1.185	0.100	0.188	−1.730
4	0.088	0.210	−0.464	0.110	0.235	−0.723	0.094	0.192	−1.053
5	0.088	0.219	−0.606	0.115	0.246	−0.945	0.099	0.202	−1.382
6	0.092	0.228	−0.756	0.119	0.255	−1.177	0.103	0.209	−1.723
7	0.096	0.227	−0.458	0.114	0.255	−0.717	0.097	0.207	−1.046
8	0.092	0.211	−0.623	0.100	0.223	−0.973	0.080	0.170	−1.426

[a]Price-cell refers to the first 8 of the 50 price scenarios.
[b]H-H refers to direct price elasticity.
[c]M-H refers to cross-price elasticity measuring the sensitivity of demand for frequent user plan to the price change of moderate user plan.

4. Conclusions

The presence of response bias impairs the results of survey research which plays a crucial role in marketing research. In this paper we propose two statistical models to detect and estimate response bias. We find that substantial bias exists for the parameters of interest if a wrong model is estimated and AIC and prediction criteria are more reliable in selecting the best approximating model.

We also apply the methodology to analyze the market survey data of demand for the service of an advanced electronic device in a developing country. We demonstrate that there is a substantial response bias in the data and the revised market take rates and price elasticities appear more reasonable than the estimates obtained based on the assumption that the respondents truly indicate their preferences.

The Monte Carlo studies (for detail, see Hsiao and Sun, 1997) demonstrate that the loss of information is negligible when one estimates a more complicated response model even data are indeed generated from random utility maximization model. Since the response bias often exist, it is perhaps advisable that at the initial data exploration stage to always start with a model that incorporate response bias as a maintained hypothesis. However, since the sources of biases are many (e.g. Lessler and Kalsbeek, 1992; McFadden, 1990) and the model we propose is applicable to detect just one kind of bias, it is important to consider other possibilities in future study.

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Appendix A. Identification of randomized response and one-sided response bias model

The randomized response model and one-sided response model are reminiscent to the mixture model in the sense that they all assume that data are generated from two or more populations mixed in varying proportions (e.g. McLachlan and Basford, 1988; Titterington et al., 1985). With a parametric

specification of π_{jn} and F_{jn}, the likelihood function can be formed in terms of the mixture densities or distributions. A model is (locally) identified if its information matrix is nonsingular (in the neighborhood of the true value) (e.g. Hsiao, 1987; Rothenberg, 1971). We demonstrate the nonsingularity of the information matrix by considering the binary case in which the randomized response model and one-side response bias model are identical. For simplicity, we shall assume that $\pi_n = \pi$. For the identification of more general cases, see Sun (1995).

Suppose the probability of responding $y_n = 1$ independent of the preference is $\pi_n = \pi$, then

$$\mathrm{P}(y_n = 1) = \pi + (1 - \pi)F_n = P_n,$$

and

$$\log L = \sum_{n=1}^{N} [y_n \log P_n + (1 - y_n)\log(1 - P_n)].$$

Therefore, the information matrix of Eq. (1.2) is defined as

$$I = -E\begin{bmatrix} \dfrac{\partial^2 \log L}{\partial \pi^2} & \dfrac{\partial^2 \log L}{\partial \pi \partial \underset{\sim}{\beta}} \\ \dfrac{\partial^2 \log L}{} & \dfrac{\partial^2 \log L}{} \end{bmatrix}, \tag{A.3}$$

where

$$\mathrm{E}\frac{\partial^2 \log L}{\partial \pi^2} = -\sum_{n=1}^{N} \frac{(1 - F_n)^2}{P_n(1 - P_n)},$$

$$\mathrm{E}\frac{\partial^2 \log L}{\partial \pi \partial \underset{\sim}{\beta}} = -(1 - \pi)\sum_{n=1}^{N} \frac{(1 - F_n)}{P_n(1 - P_n)} F'_n \underset{\sim}{x}_n,$$

$$\mathrm{E}\frac{\partial^2 \log L}{\partial \underset{\sim}{\beta}\, \partial \underset{\sim}{\beta}'} = -(1 - \pi)^2 \sum_{n=1}^{N} \frac{1}{P_n(1 - P_n)} (F'_n)^2 \underset{\sim}{x}_n \underset{\sim}{x}'_n,$$

and F'_n is the first derivative of F_n with respective to $\underset{\sim}{\beta}' \underset{\sim}{x}_n$. $\underset{\sim}{w}'_n = P_n^{-1/2}(1 - P_n)^{-1/2}[(1 - F_n), (1 - \pi)F'_n \underset{\sim}{x}'_n]$. Then Eq. (A.3) can be rewritten as $I = \sum_{i=1}^{N} \underset{\sim}{w}_n \underset{\sim}{w}'_n$. Therefore, for any arbitrary non-zero vector $\underset{\sim}{c}$, $\underset{\sim}{c}' g \underset{\sim}{c} = \sum_{n=1}^{N} a_n^2 > 0$, provided $\underset{\sim}{x}_n$ is not collinear, where $a_n = \underset{\sim}{c}' \underset{\sim}{w}_n$.

Table 8
Average prices

Installation charge	Monthly charge of high user plan	Monthly charge of moderate user plan	Monthly charge of infrequent user plan
$396	$120	$60	$24

Table 9
Household demographic variables used in analysis

Variables	Categories	Percentages
Age of respondent:	– under 35	39.3
	– 35–45	30.5
	– 46–60	20.1
	– 60 +	10.2
Beeper usage:	– own	87.9
	– not own	12.1
Education:	– high school incomplete	0.2
	– high school complete	5.5
	– technico incomplete	20.5
	– technico complete/university incomplete	29.5
	– university complete	44.2
Home ownership:	– own	11.2
	– rent	88.8
Marital status:	– married	64.8
	– single	27.6
	– widowed	3.7
	– divorced/seperated	4.0
Occupation:	– executive of a large company	4.6
	– owner of smaller company	5.4
	– lawyer/physician/other professional	7.7
	– salesperson	26.2
	– government employee	2.8
	– self-employed	13.0
	– laborer	8.6
	– home-maker	5.7
	– retired, unemployed and other	26.0
PC usage:	– own	63.5
	– not own	36.5
Sex of respondent:	– male	58.4
	– female	41.6

Appendix B. Data description

The stratified random sample consists of 1024 observations chosen from top three socioeconomic groups A, B and C in a developing country. Respondents in

group A have either fairly high socio-economic positions like well-known lawyers, doctors, top managers, investors, or they have inherited money from wealthy families. They have an average annual income of $40,000 or above. They represent 6% of the total population. Respondents in group B are people with a moderate income level obtained through employment or independent professional work. They are typically lawyers, doctors, accountants, dentists, and managers whose annual income are between $20,000 and $40,000. They represent 12% of the total population. Respondents representing group C mostly have stable jobs with an annual income between $12,000 and $20,000. They represent 28% of the total population.

At the time of the survey, only 8% of the households had regular telephone service. At the beginning of the interview, the interviewer would give a brief description of the function of this new service. There were 50 price scenarios that include a one time installation fee and monthly charges for three different user plans. (The average of each price is presented in Table 8). Only one price scenario was quoted to any given respondent. Each respondent was then asked. 'Under this price scenario, which of the user plans you would choose?'. The choice set contained four mutually exclusive and exhaustive choices: Frequent User Plan; Moderate User Plan; Infrequent User Plan; Non-User Plan.

The survey also collected socio-demographic variables of the respondents such as age, martial status, education, occupation, wealth, sex, as well as their preference ordering for this service, as shown in Table 9.

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