Assessing the Diabetes Detection Initiative for Policy Decisions

Attachment E. Technical Supplement: Methodology for Conducting Perceived Benefits Analysis

Methodology for conducting the perceived benefits analysis

The underlying behavioural model is a random utility model of consumer decision-making. The standard structure of the random utility model consists of two parts. The first part is a systematic component. The systematic component captures the effect of observable attributes of the choice, such as time to clinic, on choices. The second part of the model is the random component. The random component captures the unobservable portion of the decision. The complete indirect utility function is:

$$U = V_j\ (a^j,\ y,\ s) + \varepsilon, \quad (1)$$

where *V* is the systematic portion of utility, *y* represents income, a^j represents an attribute at level *j*, *s* is a vector of other individual characteristics and ε represents the random portion. When confronted with a cost *$P*, the individual will agree to pay if the value of the change in the attributes a^j is more valuable than the lost income (*P*). Specifically:

$$V_1(a^1,\ y - P,\ s) + \varepsilon_1 \geq V_0(a^0,\ y,\ s) + \varepsilon_0 \quad (2)$$

Otherwise, the individual will choose to keep the income and live with the original set of attributes. The process, however, is stochastic. Since the researcher cannot know everything each individual's choice is a random variable from the researcher's perspective. The observed choices are observed with a probability distribution represented by:

$$Pr(\ paying\ ) = Pr\ [\ V_1(a^1, y - P, s) + \varepsilon_1 \geq V_0(a^0, y, s) + \varepsilon_0\ ], \quad (3)$$

and *Prob(not paying) = 1 - Prob(paying)*. The maximum willingness to pay (P^*) for a change in attributes for a representative individual is found by setting $\Delta V=0$ and solving for *P*. Hanemann and Kanninen (1999) show that if one assumes that the difference between random terms is generated by a standard normal CDF, the probability that individual *i* pays for a change in the level of an attribute corresponds to a standard probit model.[1]

A more sophisticated model, which accounts for a data generating process that acquires multiple responses for each respondent would be a random effects probit model. One can envision a data collection process where several stated preference questions could be asked in a single interview. The data collection process would survey individuals using several questions changing the attributes from question to question. This method requires the researcher to replicate equation 2 for each question. In the case where there are *j* survey questions and *n* attributes the behavioural model structure would be:

[1] Hanemann, W.M. and B. Kanninen (1999): "The Statistical Analysis of Discrete-Response CV Data", in I.J. Bateman and K.G. Willis (1999).

$$V_1(a_{1,1}^{1}, a_{1,2}^{1}, \_\_\_, a_{1,n}^{1}, y - P_1, s) + \varepsilon_1 \geq V_0(a_{1,1}^{0}, a_{1,2}^{0}, \_\_\_, a_{1,n}^{0}, y - P_0, s) + \varepsilon_0$$

$$V_3(a_{2,1}^{3}, a_{2,2}^{3}, \_\_\_, a_{2,n}^{3}, y - P_3, s) + \varepsilon_2 \geq V_2(a_{2,1}^{2}, a_{2,2}^{2}, \_\_\_, a_{2,n}^{2}, y - P_2, s) + \varepsilon_0$$

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$$V_j(a_{j,1}^{j}, a_{j,2}^{j}, \_\_\_, a_{j,n}^{j}, y - P_j, s) + \varepsilon_n \geq V_{j-1}(a_{j,1}^{j-1}, a_{j,2}^{j-1}, \_\_\_, a_{j,n}^{j-1}, y - P_{j-1}, s) + \varepsilon_0$$

where the superscript denotes an attribute level offered by that pair of questions. For example, the superscript 1 attributes form one bundle of attributes and a cost, P_1, which are compared to attribute bundle denoted with superscript 0 and cost P_0. If one assumes that each observation is independently distributed $N(0,\sigma^2)$, one can pool the observations across questions and use the standard probit model to estimate the parameters.

However, there can be individual-specific responses to changing attribute levels. Modeling this feature requires the researcher to distinguish three sources of variation among individual responses: i) purely random factors that arise independently in each question; ii) random factors that are individual specific; and iii) deterministic variables such as travel distance that affect the probability of paying to change attribute levels. This correlation pattern can be captured in a random effects model (after Heckman and Willis 1975)[2] :

$$Y_{it}^{*} = \beta_0 + \sum_{j=1}^{k} X_{ij} \beta_j + \mu_i + \varepsilon_{it} \quad (5)$$

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[2] Heckman, J. J., and R. J. Willis. 1975. Estimation of a stochastic model of reproduction: An econometric approach. In N. Terleckyj (Ed.), Household production and consumption. New York: Columbia University Press.

where Y_{it}* is an unobserved latent variable, X_i is a 1 x k vector of variables representing attribute levels, and β is a k x 1 vector of coefficients. The other two terms represent error components that are mutually independent. The first, μ_i, represents an unobservable characteristic specific to individual i that does not vary among the observations from i and is $N(0,\sigma_\mu^2)$. The second, ε_{it}, is $N(0,\sigma_\varepsilon^2)$ and is a component that varies among individuals and across the observations from each individual. The observed random variable, Y_{it} is defined by:

$$Y_{it}=0 \text{ if } Y_{it}^* \leq 0, \text{and } Y_{it}=1 \text{ if } Y_{it}^* > 0. \quad (6)$$

Define $\sigma^2 = \sigma_\varepsilon^2 + \sigma_\mu^2$, $\rho = \sigma_\mu^2/\sigma^2$, and impose the normalization that $\sigma^2 = 1$. Then if $Y_i = [Y_{i1}, Y_{i2}, ..., Y_{ij}]$ is the observed sequence of choices for i, and defining $v_i = \mu_i/\sigma_\mu$ then the likelihood function for this model is:

$$P(Y_i) = \int_{-\infty}^{\infty} \prod_{j=1}^{J} \Phi \left(\left[\left(\frac{X_{ij}\ \beta}{\sigma_e} \right) + \mu_i \left(\frac{\rho}{1-\rho} \right)^{1/2} \right] [2Y_{ij} - 1] \right) x\ f(\upsilon_i)\, d\upsilon_i \quad (7)$$

where $\Phi(.)$ is the normal cumulative distribution function. In this expression, ρ represents the correlation coefficient between responses from respondent i across the questions and allows the measurement of the proportion of total variance explained by systematic correlated components. If no correlation is present, $\rho=0$ and the information can be pooled across questions without regard for the particular respondent who answered and the model parameters estimated using the standard probit model. If $\rho>0$, then use of the standard probit results in biased standard errors of the coefficients (Guilkey and Murphy 1993) and one must consider the random effects in the estimation.[3]

The likelihood function for the random effects probit for an observed sample of N Y_{it}`s is simply:

$$L = \prod_{i=1}^{N} P(Y_i). \quad (8)$$

where $P(Y_i)$ represents equation (6). As numerous authors note, the estimation of parameters is difficult due to the computation of the joint probabilities of a T-variate normal distribution, which involves evaluating T-dimensional integrals. However, by conditioning on the individual effects, this problem can be reduced to a single integral involving the product of a standard normal density and the difference of two normal cumulative density functions and solved using Gaussian quadrature procedures (Butler and Moffit 1982).[4]

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[3] Guilkey, D.K. and Murphy, J.L. (1993) - `Estimation and testing in the random effects probit model', Journal of Econometrics, 59, 301-317.

[4]Butler, J.S. & Moffit, R. (1982). Notes and comments: A computationally efficient quadrature procedure for the one-factor multinomial probit model.

Data Development

The data to support estimation of these models will be derived from the choices indicated by DDI participants when presented with sets of alternatives. To illustrate the process for the data base construction, suppose attributes have the following five dimensions:

- Time Spent Taking Test and Waiting
- Type of Test
- Test performance
- Cost of Test to Participant
- Location of Test

Hypothetical Choice Set

Dimension	Choice A	Choice B	Choice C	Choice D
Time Spent Taking Test and Waiting	4 hours	2 hours	45 minutes	0
Type of Test	Drink concentrated sugar water and use needle to draw a sample of blood from a vein into a small vial-twice	Answer seven questions	Prick finger and smear a drop of blood on test paper	No Screening
Test performance	Test is not very accurate but will help you decide whether to have a better test	Test is not very accurate but will help you decide whether to have a better test	Test is very accurate but might need another test some of the time	Not Applicable
Cost of Test to You	$10	$35	$35	No Cost
Location of Test	At work or at home if you do not work	At this health clinic	At work or at home if you do not work	Not Applicable

For this example, initially five variables will be sufficient to describe each attribute selected and not selected. However, in the analysis, other variables will need to be constructed because while time and cost are continuous variables, the others are categorical. Thus, we will transform each categorical variable into a set of dummy variables for each level of the attribute except one. For example, the type of test would include three dummy variables for each of the different blood tests and paper test would be the omitted category. Once the complete set of dummy variables has been defined and coded, there will be a vector of characteristics used to describe of each of the choices A through D. It should be noted that choice D remains invariant across sets as it represents the do nothing option. In addition, each set of vectors will also include the respondent ID to facilitate estimation of random effects models.

Perceived Benefit Component

The model developed above will be fitted to the data collected during the data collection phase of the project. It is expected that geographic, gender, age and ethnic differences will be explored using standard econometric methods and the results reported in the Final Report. For simplicity this section will work from a single representative individual.

There are two aspects to the analysis. First, there is the benefit of the program to the users. Second, the models will predict participation in the program and can, therefore, be used to predict the rate of participation in the program as the attributes of the program are changed. This is particularly useful in the context of changing costs because the model will also predict the relationship between the participation and the cost of the program as cost varies while holding attributes constant.

It is expected that the modeling will examine both linear and non-linear specifications of the attributes. Linear attributes will simply follow the usual procedures. The Marginal willingness-to-pay (MWTP) for an attribute (such as waiting time) to the representative member of the sample is simply:

$$MWTP = \frac{\beta_{i,1} * attribute_i}{\beta_{TC}} \quad (9)$$

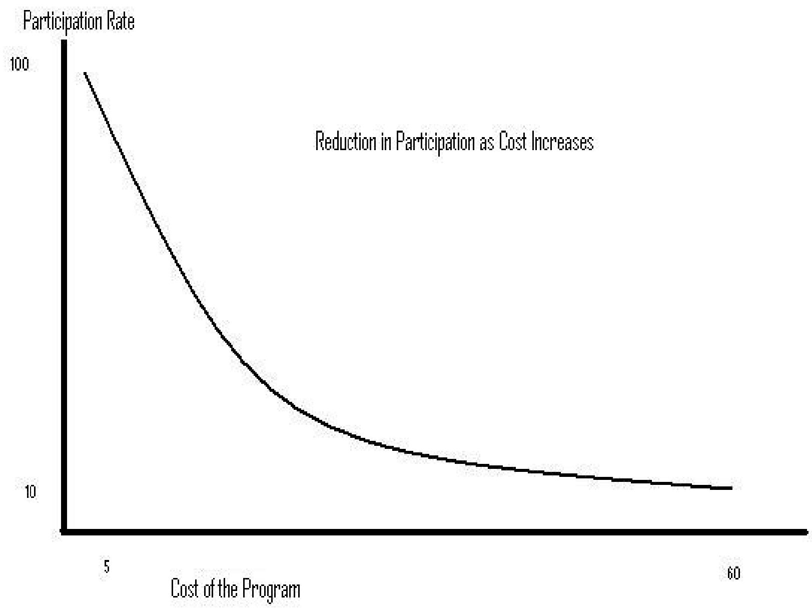
Marginal willingness-to-pay (MWTP) for a quadratic attribute is found using the following equation:

$$MWTP = \frac{\beta_{i,1} * attribute_i + \beta_{i,2} * attribute_i^2}{\beta_{TC}} \quad (10)$$

where β_1 is the parameter on congestions and β_2 congestion squared. β_{TC} is the bid coefficient. It should be noted that the same method can be applied to ethnic, age and gender effects by interacting the attribute with the demographic variable of interest. If for example one were interested in gender differences in perceived program benefits a variable that interacted gender with another attribute would be created. If this variable was significantly different from zero there would be a statistically significant difference between the sexes. The two perceived benefits (if male were coded 0 and female 1) would be:

$$\begin{aligned} Male\ \ MWTP &= \frac{\beta_{i,1} * attribute_i}{\beta_{TC}} \\ Female\ \ MWTP &= \frac{\beta_{i,1} * attribute_i + \beta_{female * attribute_i} * attribute_i}{\beta_{TC}} \end{aligned} \quad (11)$$

The second aspect of the analysis is the development of penetration curves, or participation curves. Each attribute of the program, including cost has an impact on the proportion of people who participate. Using a methodology similar to the one shown for estimating differential MWTP the probability of participation by different demographic groups for a given program can be estimated using the parameters of the model. This can be provided in a tabular of graphical format. It is useful to policymakers as it provides a very clear picture of the results of policy decisions on the success of the program. Figure 1 shows a hypothetical participation graph relating cost to participation:


Participation Rate
100
Reduction in Participation as Cost Increases
10
5
Cost of the Program
60