Using the INLOGIT Program to Interpret and Present the Results of Logistic Regressions

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Foreword

Nonlinear statistical models, of which logistic regression is one example, are often used in applied demographic analysis as well as in many other social sciences. Presentation of the results of such models can be enhanced by the calculation of predicted probabilities, or expected values of the phenomenon of interest, yet such calculations can often be rather time-consuming. This paper describes the use of a computer program, INLOGIT, which can help the applied researcher interpret and display the results of a logistic regression model.

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Models expressing nonlinear relationships among several variables at once are commonplace in applied social sciences. When research based upon such models includes the statistical estimation of parameters, the researcher must typically face the issue of how best to communicate to others both the content and the implications of the estimated parameters. In the case of a multivariate linear model, for example a least-squares multiple regression, the "content" of the results—the estimated regression coefficients—and the "implications" of the results—notably, the partial slope of the fitted regression surface with respect to one of the arguments, holding constant the other arguments—are essentially the same.

However, in nonlinear models—examples of which include logistic regressions, the Probit model, discriminant analysis, and failure-time models—the estimated parameters of the multivariate statistical model frequently do not correspond directly to an easily-interpreted concept. Typically the estimated parameters must be mapped, via some nonlinear function, into some other domain—the probability of some event, or the expected value of some potentially observable quantity—in order for their implications or practical importance to be judged. Such computations are often rather cumbersome, which may explain the fact that they frequently are omitted from reports of research findings.

This paper discusses a computer program, named INLOGIT, which can be used to calculate predicted probabilities, slopes, and elasticities in one of the nonlinear models alluded to above: the logistic regression model. The program can generate a large volume of such predictions rather quickly, and thus can assist the researcher in developing tables of results, graphical displays, and other useful interpretive material. Several special cases or unusual situations can be handled by the computer program.

In the following section of the paper, the mathematics of the multinomial logit model are summarized. This is followed by a step-by-step guide to the use and capabilities of the program. Two examples from the published literature are given in the final section.

VARIETIES OF LOGISTIC MODELS

Logistic regression models are appropriate in situations in which a realization of the dependent variable can assume one of two or more discrete (possibly ordered) categories. The independent variables can assume values from discrete and/or continuous sets. Such models have become quite popular in several social science disciplines. Particular instances of the general class of models include binary logit, multinomial logit, and conditional logit models. Recent examples from sociology include the papers by DiPrete and Soule (1986) and Halaby (1986). In demography, one recent paper using the technique is Billy et al. (1986); several additional citations can be found in Hoffman and Duncan (1986).

In economics, the logistic functional form is one of several special cases of what is often termed qualitative response or discrete choice models. A rigorous grounding of the multinomial logit model in rational choice theory has been provided by McFadden [see McFadden (1984) and additional sources cited therein]. Another survey, including citations to applied work, is that of Amemiya (1981).

A general mathematical expression for the logistic regression is as follows:

$$pr\,(y = j) = \frac{e^{z_j}}{\sum\limits_{k \in A} e^{z_k}} \tag{1}$$

where A is a set of discrete indices, y is the dependent variable, and z_j ($j \in A$) is a set of index functions. For convenience we will let A be the set $\{1,2,\ldots,J\}$, with $J \geq 2$.

The set of index functions $z_1,\ldots,z_J$ map attributes (independent variables) into the probabilities given by (1). Two polar cases can be identified. In one, the attributes belong to an individual unit (or decision maker) whose attributes—age, sex, income, education, and so on—are represented by the (column) vector X_i. In this first case

$$z_{ij} = B_j' X_i \quad , \quad j = 1,\ldots,J \quad , \tag{2a}$$

for the ith individual in the sample. Identification of the J vectors in (2a) requires imposition of a normalizing constraint, generally $B_1 \equiv 0$.

In the second case the attributes are associated with each of the J_i possible outcomes, or values of y_i (the choices or alternatives facing the ith decision maker). In this case

$$z_{ij} = B'X_{ij} \quad , \quad j = 1,\ldots,J_i \quad , \tag{2b}$$

where X_{ij} are the attributes of the jth alternative facing the ith individual in the sample—e.g. price, convenience, durability, and so on.

Intermediate cases, with both "decision-maker-specific" and "alternative-specific" variables (and associated parameters) can also be formulated. For a more complete discussion of these parameterizations, see McFadden (1984).

All of the probabilities in (1) depend on all of the parameters of the model, as well as upon the values of all the independent variables. Moreover, the partial effect of an independent variable upon one of the probabilities also depends upon all of the parameters and all the independent variables. To see this, let $D = \sum_{k \in A} e^{z_{ik}}$ and note that

$$\frac{\partial pr(y = j)}{\partial x_{km}} = p_j \frac{\partial z_j}{\partial x_{km}} - p_j \sum_{k' \in A} p_{k'} \frac{\partial z_{k'}}{\partial x_{km}} \tag{3a}$$

where x_{km} is the mth element of X_k, X_k being the attributes associated with category k of the dependent variable; in (3a) p_j is shorthand for $pr(y = j)$.

In the "decision-maker-specific" formulation given by (2a) $X_k \equiv X$, thus $\partial z_j / \partial x_{km} = \beta_{jm}$. But in the "alternative-specific" formulation given by (2b) $\partial z_j / \partial x_{jm} = \beta_m$, while $\partial z_k / \partial x_{jm} = 0$ for $k \neq j$, because z_{jm}—the mth attribute of the alternative—does not appear in z_k. Thus in the latter case expression (3a) specializes to

$$\frac{\partial pr(y = j)}{\partial x_{km}} = \beta_m p_j (1 - p_j) \quad , \quad \text{for } k = j \quad , \tag{3b.1}$$

and

$$\frac{\partial pr(y = j)}{\partial x_{km}} = -\beta_m p_j p_k \quad , \quad \text{for } k \neq j \quad . \tag{3b.2}$$

Just as the sum of the probabilities in (1) must equal one, the sum of the slopes given by (3a) or (3b.1) and (3b.2) must equal zero, which can readily be verified by summation over j in (3a).

Finally, the elasticity of a given probability with respect to changes in the values of one of the independent variables is defined as

$$\frac{\partial pr\,(y\ = j\,)}{\partial x_{jm}} \cdot \frac{x_{jm}}{p_j} \quad ,$$

which clearly depends upon all the parameters as well as the values of all the X's.

THE INLOGIT PROGRAM

The INLOGIT program will calculate probabilities, and optionally slopes and elasticities, for user-supplied parameters and attribute values. Numerous useful options are available as described below. The program is most closely geared towards the attributes-of-decision-maker specification [represented by (2a)] but can be used for an attributes-of-alternatives (or mixed) specification with appropriate definitions of program input. An example of the latter type of model is given in the following section.

In this section the program is explained step-by-step, following the flow of a typical application of the program. The first phase in such an application consists of supplying the structure and parameters of the model; the second consists of supplying values of the independent variables, and obtaining the desired calculations.

When beginning execution of the program, the user will be asked whether or not results should be written to a file (if not, only output to the screen will be obtained), and if previously created and stored parameter values/variable names are being used as input. Initially, of course, the user must supply these model specifications.

Input of model specifications. The user is asked to supply, in the following order, the following model specifications:

- number of categories of the dependent variable. The default specification, as noted earlier, is the attributes-of-decision-makers specification, with the normalization $B = 0$ imposed. This, however, is incompatible with a pure attributes-of-outcomes specification. An attributes-of-outcomes model, with J distinct types of outcomes, can be accomodated by responding to this prompt with the value $J+1$ (and by invoking certain additional options, noted below). Such a model is illustrated in the following section.

- number of explanatory variables (attributes) not including constant;
- variable names (optional); if not supplied, all prompts will be by variable number;
- names attached to categories of dependent variable (optional);
- parameter vectors. As noted above, the parameter vector B defaults to zero. The term "parameter vectors" here refers to quantities specific to each category of the dependent variable; the term "independent variables" encountered later refers to quantities fixed across categories of the dependent variable. These usages reflect the fact that the program is primarily oriented to the attributes-of-decision-maker version of the logistic model; in this orientation the mth attribute--say, an individual's age--is the same for each possible value of the dependent variable, but this attribute has a unique coefficient or "loading" in the index function of each category of the dependent variable. In order to use this program to evaluate probabilities in an attributes-of-alternatives specification, it is necessary to treat as "parameters" the attributes of a given category of the dependent variable, and as "independent variables" the estimated logistic regression coefficients—i.e. to reverse the previously-described roles of "parameter" and "independent variable".

Thus, in a prototypical discrete-choice problem, in which a single attribute, "price", is attached to each possible object of choice, the price of the first, second, ..., Jth object will be supplied in response to the program's prompt for "parameter vectors." Later, when the user is asked to supply values of the independent variables, the estimated logistic regression coefficient representing the price effect will be entered in the appropriate location in the X-vector.

INLOGIT includes a capacity to treat some independent variables as transformations of others. For each desired transformation, the user must supply the index (location in the attribute vector) of the source and target variables involved in the transformation. The menu of available transformations, all of which are self-explanatory, appears on the screen as follows:

```
enter 1 for target = k*source, k real
      2 for target = natural log(source)
      3 for target = source**k, k real
      4 for target = max[ (source - k), 0 ], k real
               (linear spline)
      5 for target = Box-Cox with parameter k
               k ne 0
      6 for indicator function
          (a)  target = I[source = k]
          (b)  target = I[ k1 <= source <= k2]
```

In each case, k (or $k1$ and $k2$) are parameters which must be subsequently supplied.

If a given independent variable enters the index functions only in nonlinear form--e.g. income appears only in logarithmic form--it may be useful to treat both "income" and "ln[income]" as independent variables, but to supply coefficients equal to zero wherever "income" appears. This will allow the user to interpret the model in terms of the untransformed variable.

Computational options. Having supplied the dimensions, parameter values, variable names, and so on, the program displays all these input values (for purposes of verification), then displays the following menu:

```
Type 1 to enter/change all x-values
     2 to change 1 x-value
     3 to delete/select a loop variable and loop range
     4 to enter/change zero-probability restriction(s)
     5 to select a set of x-s for which slopes and
       elasticities will be calculated (default=all)
     6 to run the calculations
     7 to write the current parameters, etc. to disk
     8 to edit the current parameters
     9 to go to next model/exit
```

Most of these options are self-explanatory; however, a few useful features of the program are described in more detail here.

The "looping" feature (option 3 above) allows the user to trace out the changes in all the probabilities due to changes in the value of one of the explanatory variables, while holding constant all other variables (only one loop-variable at a time can be evaluated). As a further option, the program will simultaneously produce so-called "graphics output", i.e. calculated probabilities in a form which makes easy later input into a graphics program. If this option is selected, the following further prompts will appear:

```
Do you want predicted probabilities for category 1 output?
Do you want predicted probabilities for category 2 output?
.
.
.
Do you want predicted probabilities for category J output?
```

The graphics output will be written to a file called GRAFOUT.DAT, in the following form:

```
first value of looping variable
second value of looping variable
.
.
.
last value of looping variable[1]
probability of first selected category, given first
     value of looping variable
probability of first selected category, given second
     value of looping variable
```

[1] Up to a maximum of 50 values.

```
.
.
.
probability of first selected category, given last
     value of looping variable
probability of second selected category, given first
     value of looping variable
.
.
.
and so on
```

Option 4—the zero-probability restriction--can be used to suppress any number of categories of the dependent variable. In the models of household composition reported in Wolf (1984) or Wolf and Soldo (1986), for example, there is variation within the population in the feasibility of some categories of the dependent variable: for example, "living with children" is ruled out for individuals without children. In this example, a comparison of the probabilities of selected household types, according to the existence or nonexistence of children, can be accomplished by alternatively imposing and removing a zero-probability restriction on the relevant category of the dependent variable.

The zero-probability option is also used to force the program to evaluate a pure attributes-of-alternatives specification. As noted above, if there are J alternatives in such a model, the user should specify that the model has J+1 alternatives, treating what is actually the first alternative as the second, what is actually the second alternative as the third, and so on, ending by treating what is actually the Jth alternative as the J+1th. Then, a zero-probability restriction can be imposed on the first alternative, yielding a correctly-specified model. The purpose of this procedure is to remove from the set of alternatives the one for which, by default, $B = 0$.

Options 1, 2, and 3 are used to change values of the "X"s—that is, the factors treated as constant across alternatives. Option 8 can be used to modify values of the "parameters"—that is, the factors treated as alternative-specific in the program. This option is useful when a attributes-of-alternatives specification is being evaluated, and it is desired to calculate the implications of changes in one or more attributes of one or more of the available alternatives. In this way, for example, one can assess the effects on choice probabilities of changing one or more prices in the set of alternatives comprising a discrete-choice model. A somewhat inconvenient feature of the program is the fact that it is not possible to loop over such a parameter change; each such change must be entered individually. When this option is chosen, the program will display all the current values of the parameters, with column and row indices; the user can change any of the parameters by entering, in triples, the column index, row index, and new value of the desired parameter.

Finally, option 7 can be used (at any time during execution of the program) to write out the current values of the model specifications—variable names, parameter values, and so on—to a disk file. The first time this option is selected, the information will be written to the file PARMOUT1.DAT; the second time, to PARMOUT2.DAT; and so on, up to five times. These files can later be used as input into the program, bypassing the need to reenter the relevant information. Input files must be named PARMIN1.DAT, PARMIN2.DAT, ..., PARMIN5.DAT, allowing up to five different previously-created and stored model specifications to be evaluated on a given run of the program.

TWO EXAMPLES

The first example is taken from Wolf (1984), and is a model of the household composition of never-married women aged 65-69. There are three categories of the dependent variable: (1) living alone; (2) living with others (but not with siblings and/or parents); and (3) living with siblings and/or parents. This is an attributes-of-decisionmaker model, using the following five independent variables as attributes: dummy variables indicating disability status, home ownership, being black, and being 68 or 69 years of age (in contrast to 65-67 years of age); and a continuous measure of income (in $1000s). The parameters of the model are as follows:

	(a)	(b)
Intercepts	-2.4600	-0.3280
disabled	-0.3370	-0.0100
own home	-0.1540	0.5480
black	1.8500	-0.0260
age	0.8550	0.6130
income	0.0520	-0.1170

Column (a) contains the parameters for the second category of the dependent variable, "others", while column (b) contains the parameters for the third category, "sibs/par".

Table 1 illustrates the use of INLOGIT to contrast the predicted probabilities of each category of the dependent variable according to subgroup membership. The first set of probabilities fixes the values of *disabled*, *own home*, *black*, and age at zero, and the value of *income* at $3.8 (the sample mean). For this set of values of the explanatory variables, the model implies that the probability of living alone is 0.64; of living with others, 0.07; of living with siblings/parents is 0.29. Implicit in these calculations is the fact that siblings and/or parents exist. The remaining rows of Table 1 illustrate the effects of setting each of the indicated dummy variables to 1.

Table 2 illustrates the looping feature of the program; here all dummy variables are again set to zero, while *income* loops from 0 to 8 (in $1000s). Note that at each income level a different value of the partial effect of income on each probability [labelled (p)] and a different value of the income elasticity of the probabilities [labelled (e)] appears.

Finally, Table 3 illustrates the imposition of a zero-probability restriction. Here, the probability of category 3—living with siblings and/or parents—has been fixed at zero. In other words, we are applying the model to the situation of an older woman with no surviving parents and/or siblings. The calculated probabilities of living with "others" rise only slightly; most of the probability mass formerly assigned to the category "sibs/par" now is assigned to the category "alone."

A second example is taken from McFadden (1984), and is a model of the housing market choices of elderly single men. There are three categories of the dependent variable: home owner; renter/household head; and renter/non-head. The

Table 1. Illustrative INLOGIT results: predicted probabilities of three household types; selected values of explanatory variables.

```
 Categories                    1       2       3
                             alone   others  sibs/par
 Prob hat                     0.6386  0.0665  0.2949


 Categories                    1       2       3
                             alone   others  sibs/par
 Prob hat                     0.6529  0.0485  0.2985
disabled=     1.000; (p):     0.0126 -0.0154  0.0028

 Categories                    1       2       3
                             alone   others  sibs/par
 Prob hat                     0.5296  0.0473  0.4231
own home=     1.000; (p):    -0.1189 -0.0179  0.1368

 Categories                    1       2       3
                             alone   others  sibs/par
 Prob hat                     0.4735  0.3135  0.2130
black    =    1.000; (p):    -0.2720  0.3999 -0.1279

 Categories                    1       2       3
                             alone   others  sibs/par
 Prob hat                     0.4768  0.1167  0.4065
age      =    1.000; (p):    -0.1664  0.0591  0.1073
```

category of housing unit, rather than the particular housing unit selected, is the dependent variable. Four attribute variables appear in the model: *opcost*, or out-of-pocket costs; *return*, or net expected return on equity; income, interacted with ownership status (denoted *yown*); and income interacted with renter/non-head status (denoted *ynh*). Each is considered an attribute-of-alternative variable. However, return is identically zero for both the renter/household head and the renter/non-head alternatives.

The estimated coefficients on the attribute variables are as follows: *opcost*, -4.544; *return*, 2.506; *yown*, -.055; and *ynh*, -.838. This model can easily be fit into the INLOGIT framework as follows:

(1) in response to the prompt for number of categories of the dependent variable, enter "4"—the first will be a dummy category;

(2) enter as parameters the following numbers—

	own	rent/nonhead	rent/head
intercepts:	0.	0.	0.
opcost:	(alternative-specific values desired for purposes of illustration; e.g. alternative-specific mean values)		
return:	2.506	0.	0.
income:	-0.055	-0.838	0.

(3) enter as values of independent variables the following numbers—

opcost:	-4.544
return:	(value desired for purposes of illustration)
income:	(value desired for purposes of illustration)

In other words, the two income variables can be treated as a single attribute of the decision maker; similarly, *return*, which is multiplied by zero in the index functions for the two renter categories, can be treated as an attribute of the decision maker.[2] It is also necessary to impose a zero-probability restriction on category 1, the dummy category of the dependent variable.

Having entered the model structure in the manner outlined above, it is possible to loop over both *return* and *income*, comparing the probabilities of each type of housing tenure while holding out-of-pocket costs fixed. It is also possible to examine the effects of price (*opcost*) changes, using the "parameter edit" option described earlier.

An example of a computation based upon this model is provided below; in the illustration, the values of *opcost* are as follows: for "own", *opcost* = 5.48; for "rent/nonhead", *opcost* = 1.13; for "rent/head", *opcost* = 0.93. Income is fixed at 4.3 (in $1000s), while *return* = 5.07 (in $1000s). These values in fact characterize person number 2 from the data set upon which the parameter estimates are based [see McFadden (1984), Table 3.1]. The output supplied by INLOGIT is as follows:

[2] Indeed, since both the independent variable *return* and its coefficient appear only in the index function for the alternative "own", either can be treated as the "parameter" without affecting the calculation of predicted probabilities. However, the slope and elasticity calculations will make sense only when the coefficient is treated as the "parameter".

```
Categories                  1        2        3        4
                          dummy     own    rent nh  rent h

 Prob hat                 0.0000   0.0003  0.0108   0.9889
opcost  =   -4.544; (p):  0.0000   0.0012  0.0021  -0.0034
return  =    5.070; (p):  0.0000   0.0007  0.0000  -0.0007
income  =    4.300; (p):  0.0000   0.0000 -0.0090   0.0090
```

The model implies that an individual facing such an opportunity set would become a renter/non-head with probability 0.9889; this is, in fact, the actual choice made by this observation in the data set.

Table 2. Illustrative INLOGIT results: predicted probabilities of three household types; alternative values of income.

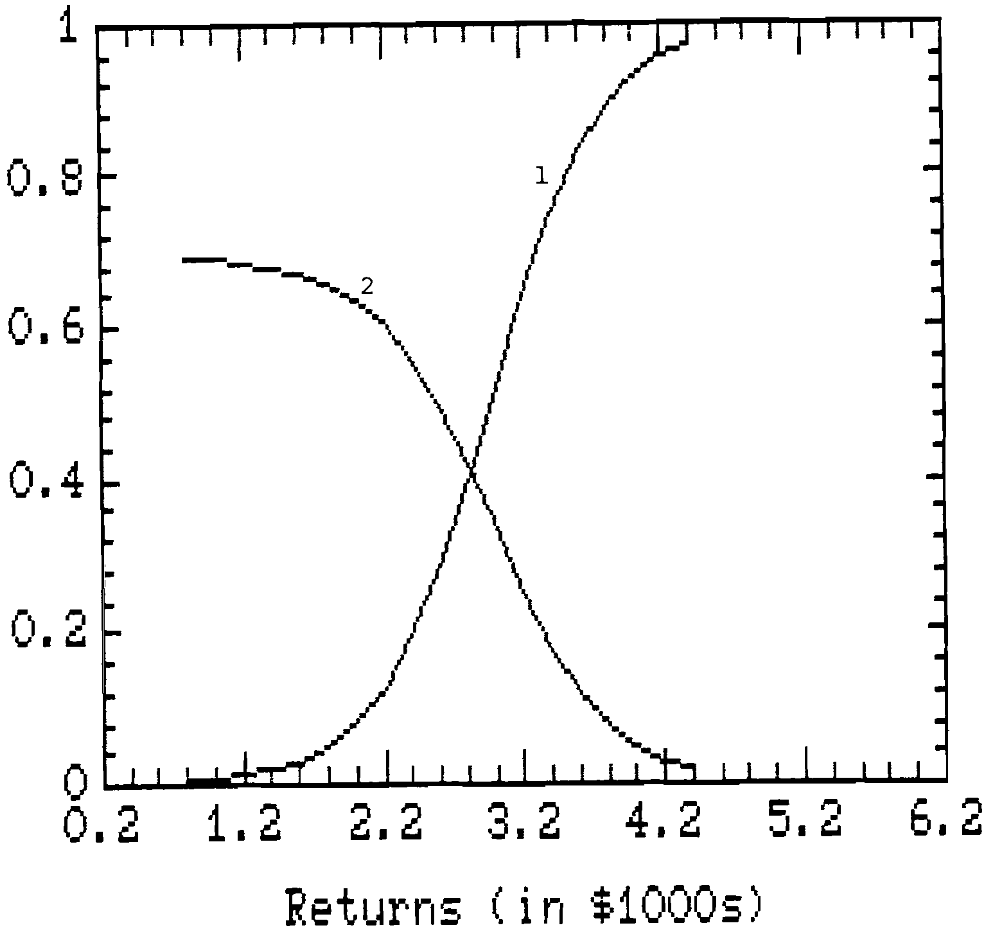
```
 Categories                  1       2        3
                           alone   others  sibs/par
 Prob hat                  0.5538  0.0473  0.3989
income  =    0.000; (p):   0.0245  0.0046 -0.0290
                    (e):   0.0000  0.0000  0.0000
 Categories                  1       2        3
                           alone   others  sibs/par
 Prob hat                  0.6006  0.0569  0.3424
income  =    2.000; (p):   0.0223  0.0051 -0.0274
                    (e):   0.0742  0.1782 -0.1598
 Categories                  1       2        3
                           alone   others  sibs/par
 Prob hat                  0.6425  0.0676  0.2899
income  =    4.000; (p):   0.0195  0.0056 -0.0251
                    (e):   0.1216  0.3296 -0.3464
 Categories                  1       2        3
                           alone   others  sibs/par
 Prob hat                  0.6786  0.0792  0.2422
income  =    6.000; (p):   0.0164  0.0060 -0.0225
                    (e):   0.1453  0.4573 -0.5567
 Categories                  1       2        3
                           alone   others  sibs/par
 Prob hat                  0.7082  0.0917  0.2001
income  =    8.000; (p):   0.0132  0.0065 -0.0197
                    (e):   0.1491  0.5651 -0.7869
```

Table 3. Illustrative INLOGIT results: predicted probabilities of two household types, with zero-probability restriction imposed; alternative values of income.

```
Categories                        1        2        3
                               alone   others  sibs/par
Prob hat                       0.9213   0.0787   0.0000
income  =     0.000;  (p):    -0.0038   0.0038   0.0000
                      (e):     0.0000   0.0000   0.0000
Categories                        1        2        3
                               alone   others  sibs/par
Prob hat                       0.9134   0.0866   0.0000
income  =     2.000;  (p):    -0.0041   0.0041   0.0000
                      (e):    -0.0090   0.0950   0.0000
Categories                        1        2        3
                               alone   others  sibs/par
Prob hat                       0.9048   0.0952   0.0000
income  =     4.000;  (p):    -0.0045   0.0045   0.0000
                      (e):    -0.0198   0.1882   0.0000
Categories                        1        2        3
                               alone   others  sibs/par
Prob hat                       0.8955   0.1045   0.0000
income  =     6.000;  (p):    -0.0049   0.0049   0.0000
                      (e):    -0.0326   0.2794   0.0000
Categories                        1        2        3
                               alone   others  sibs/par
Prob hat                       0.8853   0.1147   0.0000
income  =     8.000;  (p):    -0.0053   0.0053   0.0000
                      (e):    -0.0477   0.3683   0.0000
```

Graphs based on output from the looping feature of INLOGIT are displayed in Figures 1 - 3. In Figure 1 all variables are fixed at their alternative-specific mean values: for "own", *opcost* = 3.44; for "rent/non head", *opcost* = 0.97; for "rent/head", *opcost* = 1.96. Income is fixed at the sample mean, 6.4. Here, we vary *return* from 0.8 to 4.4 (in $1000s). Probabilities for the first and third categories of housing tenure are plotted. The curves reveal that when returns to equity are low, the probability of being a renter/household head is high (over 0.7), falling rapidly as returns rise above 2.2. Over this range of returns, the probability of being a homeowner rises from (effectively) 0 to 1. Figure 2 uses all the same values as does Figure 1, with one exception: the value of *opcost* for renter/household heads is reduced to 1.5, about 75 percent of the sample mean. The effect is to shift the probability-of-ownership curve to the left, while shifting the left tail of the curve representing the probability of being a renter/household head upwards. The probability of being a renter/non-head (which is not shown in the Figures) essentially vanishes in Figure 2.

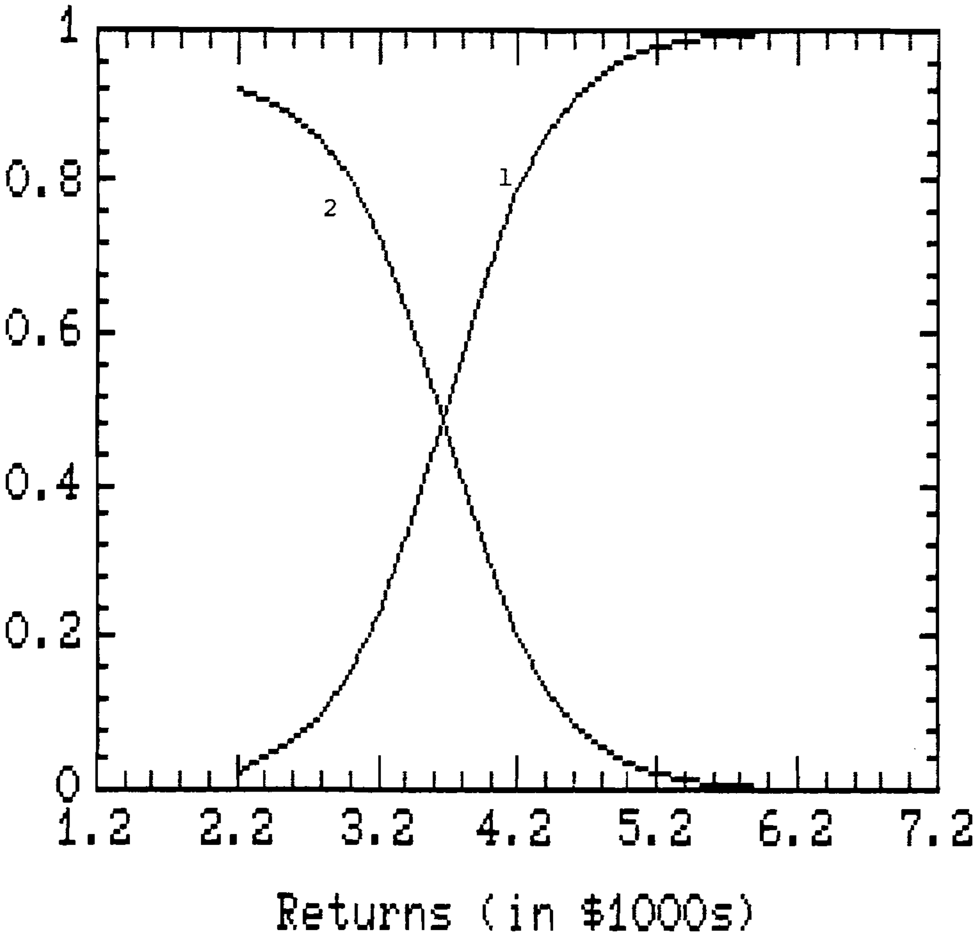
Figure 1. Pedicted housing market choices varying returns to home ownership.



key: 1 = probability of being a homeowner
2 = probability of being a renter/household head

Finally, Figure 3 is based upon values of *opcost* which are fixed at their alternative-specific sample mean values, while we loop over values of income from $0 to $15,000. At zero income, the most probable housing-market choice is renter/non head. This is quickly surpassed by the probability of being a homeowner, which peaks at about $6000 annual income, falling slightly thereafter.

Figure 2. Pedicted housing market choices varying returns to home ownership.

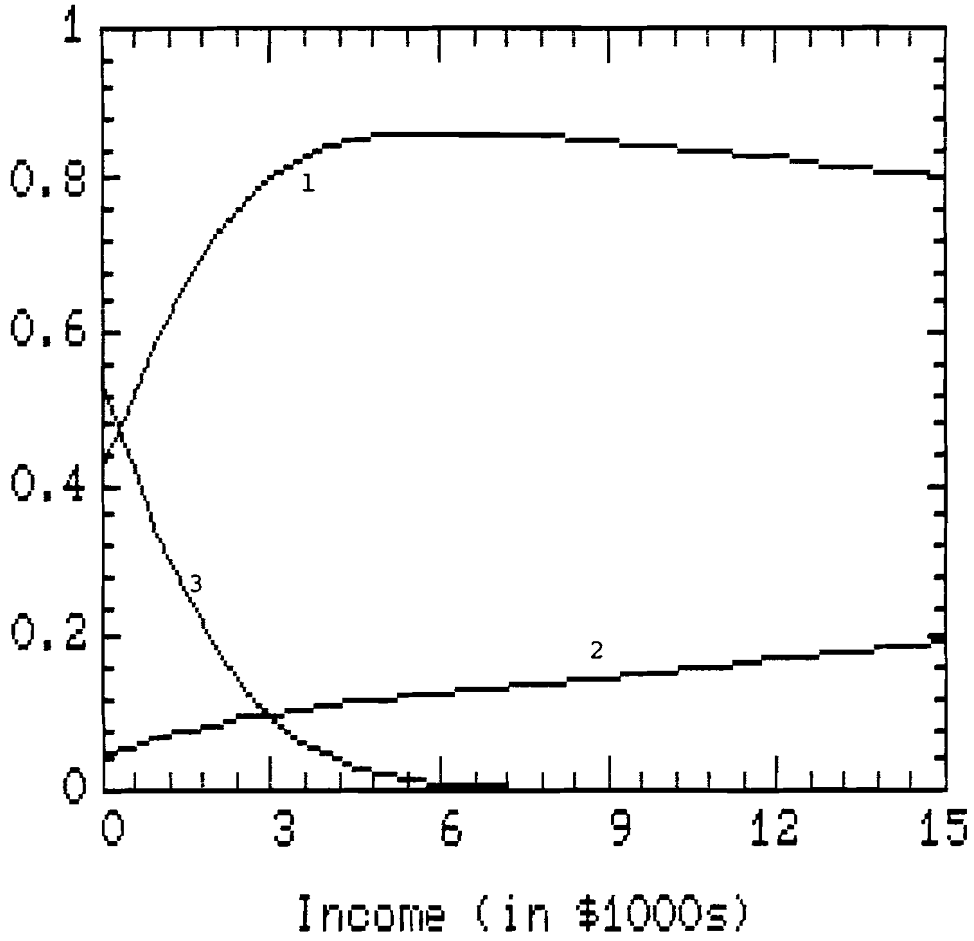


key: 1 = probability of being a homeowner
2 = probability of being a renter/household head

AVAILABILITY OF PROGRAM

INLOGIT is written in Fortran, and is available to any interested user who sends the author a blank diskette. The source code, an executable program module, and input files allowing the user to recreate the two examples discussed above will be supplied. The executable module has been compiled using the IBM Profort compiler, and requires an 8087 coprocessor in order to execute. Some source code statements may have to be changed in order to have the program successfully compile with other compilers.

Figure 3. Pedicted housing market choices varying income.



key: 1 = probability of being a homeowner
2 = probability of being a renter/household head
3 = probability of being a renter/non head

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