Modeling Discrete Choice With Response Error: Food Stamp Participation

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Validation of Food Stamp program participation by Marquis and Moore revealed net bias of 13% in mean estimates of participation in the *1984 Survey of Income and Program Participation.* We extend the analysis, incorporating demographic and economic covariates in models for underreporting and overreporting. We use the resulting models of response error to refine estimates of participation models using pseudo–maximum likelihood estimation methods. We find that the probability of underreporting rises with increased family income. Estimates of the participation model indicate the presence of substantial bias in income- and asset-related parameters compared to values obtained without incorporating response error.

KEY WORDS: Measurement error; Probit; Pseudo maximum likelihood; SIPP.

1. RESPONSE ERRORS IN PROBIT

Models of Food Stamp program participation are of practical interest to policy makers. Estimated participation models are used to analyze the extent of food stamp use among the eligible population and to provide forecasts of the effects of proposed changes in program structure (National Research Council 1991). Typically, standard threshold-crossing models of Food Stamp participation lead to maximum likelihood estimation of a probit or multivariate probit (Blank and Ruggles 1993; Fraker and Moffitt 1988; Hagstrom 1991; Martini 1992). Estimation is usually based on self-reported survey measures of participation.

The failure of some survey households to report program participation is well documented. Counts of aggregate participation from the *Panel Survey of Income Dynamics,* the *Consumer Expenditure Survey,* and the *Survey of Income and Program Participation* systematically fall short of counts of Food Stamp program participants derived from administrative records of the Food and Nutrition Service (Trippe, Doyle, and Asher 1992, table II.1). Marquis and Moore (1990) used administrative record data from three states to estimate probabilities of error in reporting participation for eight government programs to the *Survey of Income and Program Participation.* They found that respondents underreport Food Stamp participation by 19%.

Surveys are essential to modeling differential participation rates of households, because nonparticipants are excluded from administrative records. Estimation of participation models is logically restricted to *eligible* households. Survey data are necessary to identify all of these households. The *Survey of Income and Program Participation* was designed specifically to estimate the eligible population for programs such as Food Stamps (National Research Council 1993).

Respondents' reports of participation contain both errors of omission (false negatives) and errors of commission (false positives). These errors imply that probit models of Food Stamp participation estimated from survey data by maximum likelihood methods are biased, because they do not take response errors into account. Such estimates should be reexamined to obtain unbiased estimates. Assessing the extent of bias is a scientifically important undertaking, because it will validate early work or establish superior estimates.

The need to incorporate information about response errors in modeling economic data was recognized 30 years ago by Ferber and colleagues (Ferber, Forsythe, Guthrie, and Maynes 1969a,b) and by Morgenstern (1963). Bias in the estimation of linear models with response errors is well understood (Fuller 1987), and validation data have been used to examine the effect of response error in explanatory variables in a linear regression setting (Bound and Krueger 1992; Duncan and Hill 1985). But estimation of probit models with response error in the dependent variable is not well understood (Carroll, Ruppert, and Stefanski 1995), and studies that use validation data to establish the extent and structure of the bias do not exist. We address this deficiency in the literature.

This research estimates a probit model of Food Stamp participation accounting for response error in the survey measure of participation. We hypothesize that the rate of response error is not independent of participation and other variables. Models of response error are first estimated on the validation sample; that is, a sample of the population that measures both true participation and the survey response. We then use the response error models in pseudo–maximum likelihood estimation of the Food Stamp participation model. This model is estimated on the primary sample, which contains information necessary to identify all eligible households. That information is not available in

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the validation sample, which is collected for a different reference period than the primary sample and uses the same survey instrument as the primary sample.

Findings of systematic relationships between household characteristics and response errors are robust and significant. Modeling the likelihood of participation conditional on individual probabilities of response errors produces estimates that are significantly different from estimates that do not condition on probabilities of response errors. We conclude that explicit models of response error can assist in modeling survey data, even when validation data are sampled at a different time and on a different universe from the survey data.

This article is organized as follows. Section 2 presents the data and explains critical conditioning variables. Section 3 develops the model of Food Stamp participation and establishes the relationship between the participation model and the models of reporting error. The section briefly discusses asymptotic properties of the pseudo–maximum likelihood approach used to estimate the model of Food Stamp participation. Section 4 presents estimates of three models, two models describing response error and one model describing Food Stamp participation behavior.

2. DATA

Both the primary sample and the validation sample derive from the 1984 *Survey of Income and Program Participation.* This survey encompasses approximately 20,000 households. Interviews were taken every 4 months, for a maximum of 36 months that included all of 1984 and 1985.

Table 1. Primary Sample Statistics

Variable	*Mean*	*Std. dev.*
Food stamp response indicator	.098	.30
Resources and needs ($/month)		
Income per capita	547	442
Poverty threshold	871	250
Predicted wage rate ($/hour)		
Husband	13.27	3.62
Below mean	12.07	1.59
Above mean (value − mean)	1.19	2.74
Wife	7.39	1.62
Below mean	6.77	1.03
Above mean (value − mean)	.62	.89
Net wealth ($)		
Countable assets[a]	393	473
Equity in owned home[b]	17,172	26,425
≤ $75,000	15,973	22,017
> $75,000	1,200	8,473
Other wealth	6,717	29,377
≤ $75,000	4,752	15,801
> $75,000	1,965	18,363
Other demographic		
Number of Children under 18[c]	1.46	1.32
Disabled head indicator[d]	.12	.33
Living in MSA[d]	.45	.50

NOTE: The primary sample consists of asset-eligible married couples, both spouses 18–24 (N = 2,624), from the August–November 1984 Survey of Income and Program Participation.

[a] Countable assets contain assets that determine eligibility for the Food Stamp program (see text).

[b] Owners' mean equity is $31,500; owners constitute 54.4% of the asset-eligible households.

[c] Households containing children constitute 70.8% of the asset-eligible households.

[d] Indicator = 1 if the condition is true, 0 otherwise.

2.1 The Primary Sample

The primary sample is drawn from the fourth wave (9 months after the first interview for 25% of the sample, 12 months after the first interview for the remainder). Households in which both husband and wife were of working age (18–64) are included. Households whose assets exceeded the threshold for eligibility for Food Stamp program are excluded. Asset eligibility can be established only at the fourth and seventh waves, when questions are asked about asset holdings and debt.

The administrative unit for the Food Stamp program includes all household members who share food and cooking arrangements. Martini (1992) found that the household and the administrative unit for the Food Stamp program are the same in nearly all cases. In 1984 Food Stamp eligibility required, among other things, that gross income must fall below 130% of the official poverty line (except for units containing an aged or disabled person) and that countable "liquid" assets must be less than $1,500, or $2,000 for units containing aged or disabled persons. (See U.S. House of Representatives 1994 for details of the eligibility rules.)

Participation is modeled on predetermined variables, to give a reduced form that is suitable for forecasting (see Sec. 3.). Thus we choose *predicted* earnings as an independent variable rather than the realized earnings, which are jointly determined with Food Stamp participation. Predicted earnings are conditional means estimated separately for husbands and wives from human capital models (Killingsworth 1983). The models predict wage rates from schooling, experience on the job, and family life cycle. They provide predictions for persons who are out of the labor force as well as for employed persons. The estimation procedure controls for selectivity in the observed earnings (Heckman 1979).

Table 1 presents means and standard errors for the primary sample. The six rows titled "predicted wage rate" summarize the conditional expectations discussed in the previous paragraph. The mean predicted hourly wage for husbands is $13.27, an average over both working and nonworking husbands. A spline with a knot at the mean predicted wage rate for husbands generates two variables shown in the two following rows. The spline allows for nonlinear responses to the predicted wage. The next three rows describe predicted wages for wives.

Three variables that sum to net wealth are included in the analysis: countable assets, home equity, and other wealth. "Countable assets" contains all assets that determine eligibility for the Food Stamp program, including checking accounts, savings accounts, stocks, and bonds, less associated debt. "Home equity" is the self-reported value of the house owned by the householder less the amount of outstanding mortgages. "Other wealth" contains net wealth from automobiles, businesses, second homes, and other sources that are not counted in the other two categories. Home equity and other wealth are fit as linear splines with a knot of $75,000 to allow nonlinear responses and to reduce the effect of wealthy households. Few households have that level of wealth, and we did not want their behavior to affect the estimated responses of less wealthy households.

The poverty threshold is the Office of Management and Budget determination of the level of income below which families are considered poor in the United States (National Research Council 1995). It varies by family size and is adjusted for inflation by the Census Bureau.

2.2 The Validation Sample

The validation sample was collected by Marquis and Moore (1990). Individuals interviewed at the first and second wave of the 1984 *Survey of Income and Program Participation* panel were matched to a census of administrative records in three states selected for their willingness to supply high-quality, machine-readable administrative records. The match was based on Social Security number, name, address, age, and gender. The analysis here focuses on validation data for the first interview, because those data are not subject to attrition. Further, the number of additional households reporting Food Stamp participation in the second interview is small. Estimates of models of response error for the first and second interviews showed no detectable differences.

We aggregate the validation sample to the household level. Errors resulting from confusion among household members about who is the authorized recipient of food stamps are not of interest here. As long as some household member reports the participation, model estimates are not affected. Aggregation to the household unit results in a decrease in both errors of omission and errors of commission. Marquis and Moore (1990) found that 22% of Food Stamp participants in the last month prior to the first interview commit errors of omission and .36% of nonparticipants commit errors of commission. When individual responses are aggregated to the household level, errors of omission are 12% and errors of commission are .32%. The second and third rows of Table 2 display the discrepancy between aggregate survey responses and the matching administrative records.

Table 2 presents means and standard deviations for the validation sample and for the partitions *participants* and *nonparticipants.* According to administrative records, 181 households received Food Stamps during the reference month. This participant sample is the basis for modeling errors of omission. Nonparticipants (2,504 households) are used to model errors of commission.

Per capita income (i.e., the total household income from all sources divided by the number of household members) is used to model both errors of commission and errors of omission. In addition, gender and marital status are used to analyze errors of omission. Per capita income provides a better fit than income and household size. Other regressors, including education and race of the person certified to receive food stamps, do not add significantly to the models presented.

The validation sample does not represent a region, or the United States, because of the multistage sample used for the *Survey of Income and Program Participation.* This is a potential problem, but estimates of the relationship between response errors and economic and demographic variables will be unbiased if the form of the relationship is correctly specified.

3. FRAMEWORK FOR THE MODELS

Households eligible for Food Stamps choose to participate if the benefits of participation outweigh the costs. Income level, asset holdings, and the decision to participate in the Food Stamps program are simultaneously determined by each household. The participation response analyzed is for the month prior to interview. We measure asset eligibility by asset holdings at the time of the interview. Thus we model participation conditional on the outcome of asset decisions made in the month prior to the interview.

Table 2. Validation Sample Statistics

	All		Administrative record shows Food Stamp: Nonparticipant		Administrative record shows Food Stamp: Participant	
Attribute Sample N	2,685		2,504		181	
	$\bar{x}$	s	$\bar{x}$	s	$\bar{x}$	s
Received Food Stamps						
Survey response	.06	.24	.003	.056	.88	.33
Administrative record	.07	.25	0	0	1	0
Resources, needs						
Per capita income ($)	932	1,672	982	1,720	232	167
Demographics						
Gender female[a]	.30	.46	.27	.44	.73	.45
Married, spouse present[b]	.61	.49	.63	.48	.28	.45
Gender female·married	.04	.20	.03	.18	.12	.32
Mean age of head (years)	49	18	50	18	38	17
Proxy response	.26	.44	.26	.44	.15	.36

NOTE: The validation sample consists of households in Florida, Pennsylvania, and Wisconsin during wave one of the Survey of Income and Program Participation. These individuals were matched to administrative records from these three states.

[a] Equals 1 if participant is female or nonparticipant householder is female.

[b] Equals 1 if participant is married, or nonparticipant householder is married.

[c] Equals 1 if proxy.

A standard threshold-crossing model leads to the familiar probit specification

$$\Pr[y_{ti}^* = 1] = F(\mathbf{X}_{ti}\boldsymbol{\beta}_f), \tag{1}$$

where y_{ti}^* is an indicator variable at time t for the true participation of the ith household and $F(\cdot)$ is the cumulative normal distribution function. The vector $\mathbf{X}_{ti}$ contains variables thought to affect the costs and benefits of a household's participation in Food Stamps. This model was formulated to gain insight into the impact of assets excluded from the eligibility test on the choice to participate. That impact has not been consistently treated in earlier work (David and MacDonald 1992; Martini 1992, table A.1). The specification differs from other work in two important ways. First, *all* asset-eligible households are included. Second, predicted wages and net asset holdings are used. These variables, in combination with the poverty threshold and number of children in the household, are suggested by theoretical models of household choice (Deaton and Muellbauer 1980, chaps. 3 and 8). They also serve as a proxy for a more precise calculation of the potential benefit from Food Stamps. Because the level of income reflects labor market choices made concurrently with the decision to participate, and because countable assets alone do not reflect the potential yield of wealth, prior univariate probit specifications are flawed in their choice of regressors as well as their choice of sample.

Let y_{ti} be an indicator variable for reported participation, including response errors. Bayes's rule relates the survey response, y_{ti}, to y_{ti}^*:

$$\begin{aligned}\Pr[y_{ti}=1] &= \Pr[y_{ti}=1|y_{ti}^*=1]\cdot\Pr[y_{ti}^*=1]\\ &\quad+\Pr[y_{ti}=1|y_{ti}^*=0]\cdot\Pr[y_{ti}^*=0].\end{aligned} \tag{2}$$

Let p_{ti} and q_{ti} denote the probabilities of errors of commission ($y_{ti} = 1|y_{ti}^* = 0$) and omission ($y_{ti} = 0|y_{ti}^* = 1$) for the ith household at time t. We assume that (p_{ti}, q_{ti}) are conditional only on attributes of the ith household at time t. Substituting the participation probability from Equation (1), Equation (2) can be written as

$$\Pr[y_{ti}=1] = (1-p_{ti}-q_{ti})\cdot F(\mathbf{X}_{ti}\boldsymbol{\beta}_f) + p_{ti}. \tag{3}$$

Equation (3) implies the following likelihood function for the primary sample data:

$$\begin{aligned}&\ln\mathcal{L}(\mathbf{p},\mathbf{q},\boldsymbol{\beta})\\ &= \sum_{i=1}^{N} y_{4i}\cdot\ln((1-p_{4i}-q_{4i})\cdot F(\boldsymbol{\beta}_f\mathbf{X}_{4i})+p_{4i})\\ &\quad+(1-y_{4i})\cdot\ln((1-p_{4i}-q_{4i})(1-F(\boldsymbol{\beta}_f\mathbf{X}_{4i}))+q_{4i}),\end{aligned} \tag{4}$$

where $\mathbf{p},\mathbf{q}$ are stacked vectors of p_{ti} and q_{ti}.

The unknown parameters $(p_{4i}, q_{4i}, \boldsymbol{\beta}_f)$ are unidentified without further information. The approach taken here is to use the validation sample from the first interview to estimate (p_{1i}, q_{1i}). Values of $(\hat{p}_{4i}, \hat{q}_{4i})$ are calculated using attributes of the ith household at the fourth interview and the estimated models for response errors.

3.1 Errors of Omission

Omissions may occur because information is inaccessible to the respondent or because the respondent is unwilling to reveal sensitive information; that is, facts that may stigmatize or threaten the respondent (Eisenhower, Mathiowetz, and Morganstein 1991). We hypothesize that response errors are related to household characteristics that vary widely in the population. First, errors of omission are more likely when the respondent is at a higher income level, where food stamp use is not prevalent or where fraud may be involved. Per capita income may proxy for sensitivity and level of program benefit. The quantitative importance of each of these sources of the observed relationship cannot be identified. Second, the survey process gives more opportunities for detecting program participation among married couples, where both husband and wife are interviewed, than among households where the food stamp recipient is not married, because other adults in the household may be less well informed about the food stamp recipient than a spouse would be. Third, we believe that the person who actually uses food stamps has a tangible reminder of program participation and will more frequently offer a correct response than will another adult who may be the certified recipient but who buys little food. We expect that in a married-couple household, the wife is more likely to use food stamps than the husband. Hence we hypothesize that women will give better reports than men among married couples, but that this gender effect will not be so strong for single food stamp recipients. Finally, we hypothesize that participation will be more accurately reported by the person receiving the stamps than by a proxy, because we expect proxies to be less well informed. The opposite effect could be observed if the legal recipient of food stamps suffers more stigmatization than the proxy and the proxy is well informed.

These hypotheses lead to the following probit for errors of omission:

$$q_{1i} = \Pr[y_{1i}=0|y_{1i}^*=1] = F(\mathbf{Z}_{1i}^q\boldsymbol{\beta}_q). \tag{5}$$

The vector $\mathbf{Z}_{1i}^q$ includes gender, marital status, gender–marital status interaction, an indicator for proxy interview—each defined for the respondent reporting recipiency or the householder where multiple reports or no reports were made—and per capita income for the ith household at the first interview. Estimates are obtained from the participant sample (Table 2, columns 5 and 6).

3.2 Errors of Commission

Hypotheses for errors of commission again relate to per capita income. Households with sufficient income to be at little or no risk of requiring economic assistance do not use Food Stamps and have no difficulty giving a negative response. Households who receive any kind of assistance could confuse programs or telescope past events forward or backward in time, thereby committing an error. Because errors of commission are rare, it is difficult to estimate multivariable relationships. The probit for errors of commission is

$$p_{1i} = \Pr[y_{1i} = 1 | y_{1i}^* = 0] = F(\mathbf{Z}_{1i}^{(p)} \boldsymbol{\beta}_p), \quad (6)$$

where $\mathbf{Z}_{1i}^{(p)}$ includes per capita income. Estimates are obtained from the nonparticipant sample (Table 2, columns 3 and 4).

Errors of commission may be limited to the eligible population. But no logical hypothesis implies that ineligible households commit no errors. A probit on per capita income causes the probability of errors of commission to change nonlinearly, and we cannot identify any boundary that delimits the population at risk for this type of error.

3.3 Participation

The likelihood function in Equation (4) is constructed using the predicted values $(\hat{p}_{4i}, \hat{q}_{4i})$, and estimation of the parameter $\boldsymbol{\beta}_f$ is achieved by maximization of this pseudolikelihood. Pseudolikelihood estimation has a long history in statistics and econometrics (Gourieroux, Monfort, and Trognon 1984; Nelder and Lee 1992). It is consistent and asymptotically efficient.

Because the predicted values $(\hat{p}_{4i}, \hat{q}_{4i})$ are functions of the estimated parameters $\hat{\boldsymbol{\beta}}_p$ and $\hat{\boldsymbol{\beta}}_q$, the asymptotic variance of $\hat{\boldsymbol{\beta}}_f$ will be a function of the asymptotic variances of $\hat{\boldsymbol{\beta}}_p$ and $\hat{\boldsymbol{\beta}}_q$. First-order conditions for the maximization of the pseudolikelihood function are approximated by a linear Taylor expansion about the true parameters $(\boldsymbol{\beta}_f, \boldsymbol{\beta}_p, \boldsymbol{\beta}_q)$:

$$0 \simeq \bar{\mathbf{Z}} + \bar{\mathbf{I}} \cdot (\hat{\boldsymbol{\beta}}_f - \boldsymbol{\beta}_f) + \bar{\mathbf{U}}_p \cdot (\hat{\boldsymbol{\beta}}_p - \boldsymbol{\beta}_p) + \cdot \bar{\mathbf{U}}_q \cdot (\hat{\boldsymbol{\beta}}_q - \boldsymbol{\beta}_q), \quad (7)$$

where $\bar{\mathbf{Z}} = 1/N \sum_{i=1}^{N} (\partial \ln \mathcal{L} / \partial \beta_f), \bar{\mathbf{I}} = \partial \bar{Z} / \partial \beta_f, \bar{\mathbf{U}}_p = \partial \bar{Z} / \partial \beta_p, \cdot \bar{\mathbf{U}}_q = \partial \bar{Z} / \partial \beta_q$. The limiting distribution of the parameters can then be derived using standard asymptotic results:

$$\sqrt{N}(\hat{\boldsymbol{\beta}}_f - \boldsymbol{\beta}_f) \to N(0, \mathbf{V}), \quad (8)$$

Table 3. Models of Omission Errors

Coefficient	*Model* O1	*Model* O2
Intercept	−1.570*	−.865
	(.216)	(.372)
Per capita income ($\$\cdot 10^3$)	1.56*	1.592*
	(.656)	(.702)
Gender female		−.783*
		(.353)
Married, spouse present		−.662
		(.501)
Gender-Female·Married		.845
		(.632)
Proxy response		−.816
		(.480)
Log-likelihood	−64.20	−60.21

NOTE: Food Stamp participants from validation sample, N = 181 Dependent variable = 1 if false negative.
* Significant at the 5% level.

where

$$\mathbf{V} = \mathcal{I}^{-1}(\mathcal{I} + K_p \cdot \mathcal{U}_p \cdot \mathbf{V}_p \cdot \mathcal{U}_p' + K_q \cdot \mathcal{U}_q \cdot \mathbf{V}_q \cdot \mathcal{U}_q') \cdot \mathcal{I}^{-1}. \quad (9)$$

The scalar coefficients K_p and K_q are the limits of the ratios of the sample size in the primary sample, N, to the sample sizes used in estimation of the models of reporting error in the first stage. The matrices $\mathcal{I}, \mathcal{U}_p$, and $\mathcal{U}_q$ are the probability limits of $\bar{\mathbf{I}}, \bar{\mathbf{U}}_p$, and $\bar{\mathbf{U}}_q$. The matrices $\mathbf{V}_p$ and $\mathbf{V}_q$ are the asymptotic variance matrices from the estimates $\hat{\boldsymbol{\beta}}_p$ and $\hat{\boldsymbol{\beta}}_q$.

Only actual participants in the Food Stamp program are used to estimate $\boldsymbol{\beta}_q$. Only actual *nonparticipants* are used to estimate $\boldsymbol{\beta}_p$. Therefore, the covariance between $\hat{\boldsymbol{\beta}}_q$ and $\hat{\boldsymbol{\beta}}_p$ is 0. We assume that the covariance between $\bar{\mathbf{Z}}$ and $(\hat{\boldsymbol{\beta}}_p, \hat{\boldsymbol{\beta}}_q)$ is also 0. The term $\bar{\mathbf{Z}}$ is a function of the primary data sample, whereas $\hat{\boldsymbol{\beta}}_p$ and $\hat{\boldsymbol{\beta}}_q$ are functions of the validation sample. We argue that the covariance term makes a small contribution to $\mathbf{V}$. The validation sample is not a subsample of the primary sample, because unmarried adults are included and validated responses pertain to a reference period 9 or 12 months earlier (see Sec. 2.1).

All of the terms in $\mathbf{V}$ are easily estimated by their sample analogs. We note that standard errors estimated using the formula in Equation (9) are not qualitatively different from the estimated $\mathcal{I}^{-1}$. We find that the estimates of $\mathcal{U}_p$ and $\mathcal{U}_q$ are nearly 0 in the primary sample. This finding also supports our earlier assertion that the covariance terms omitted have small effects.

4. EMPIRICAL RESULTS

4.1 Models of Response Error

Table 3 displays estimates of two models of errors of omission. Model O1 is parsimonious, using only per capita income of the household as a regressor. Model O2 adds three attributes of the respondent/householder: gender, marital status, and proxy interview.

Higher per capita income leads to higher probability of an error of omission in both specifications. This result does not provide evidence for the underlying causes. Cognitive research on responses suggests that small payments may not be salient and participation may be a sensitive subject. Model O2 supports a significant effect for gender. Female-headed households have a lower probability of making an error of omission. The likelihood ratio test for the joint effect of the three demographic variables is not significant at the 5% level. This small sample does not confirm our hypotheses.

Although the finding is only significant at the 10% level, proxy interviews lead to lower response errors than self-reports. One mechanism that is consistent with this counter-intuitive finding is "cooperativeness." The least cooperative respondents refuse to give an interview or make themselves inaccessible. More cooperative respondents will give an interview for themselves. The most cooperative respondents offer to provide proxy information for others who cannot be contacted.

Table 4. Model of Errors of Commission

Coefficient	Model C1
Intercept	−1.876 (.234)
Per capita income ($\$\cdot 10^3$)	−1.677* (.562)
Log Likelihood	−46.24

NOTE: Food Stamp nonparticipants from validation sample, N = 2,504. Dependent variable = 1 if false positive.
* Significant at the 5% level.

Table 4 displays estimates of a model for errors of commission. Unlike the participation models estimated in the next section, the sample here includes both eligible nonparticipants and ineligibles. Because errors of commission are rare, reliable modeling of their relationship to personal characteristics is difficult. Nonetheless, Model C1 shows a strong inverse relationship between misreporting and per capita income. To bound bias that might arise from including large numbers of households where the probability of Food Stamp participation is almost 0, we censored the sample to exclude households whose income exceeds 130% of the poverty line. Half of the errors of commission were discarded, but the coefficient on per capita income was unchanged. This finding gives us some confidence that the probit specification for nonparticipants is not an artifact arising from the inclusion of irrelevant cases. Although the probability of error of commission predicted from this model is small, consistent estimation requires both $\hat{p}_{4i}$ and $\hat{q}_{41}$ in Equation (4).

4.2 Models of Food Stamp Participation

We estimated the participation model using five different models for the probabilities of response errors, $\{\hat{p}_{4i}, \hat{q}_{4i}\}$. Model A is the naive assumption typically used by researchers; data include no response errors. Model B uses the mean error rates in the validation sample; response errors are assumed to be independent of all observed covariates. A common technique for adjusting probit models like A to known aggregate benchmarks is to increase predicted probabilities of participation by a constant $k \equiv N/\hat{n}$, where N is the benchmark and $\hat{n}$ is the point estimate of the number of recipients obtained through the survey. In general, these estimates will not be probabilities. Model B is an alternative to that procedure. Model C uses the mean error rates for married couples; error rates are conditional only on marital status. Model D predicts error rates from Models O1 and C1; response error is conditioned on per capita income of each household. Model E predicts error rates from Models O2 and C1; errors of omission are conditioned on per capita income, marital status, gender, and proxy status, whereas errors of commission are conditioned on per capita income. Table 5 presents the mean and standard deviation of predicted response errors in the primary sample for each of the five models. Estimates for Models A–C are reported in Table 6; estimates for Models D and E, in Table 7.

Estimates for Model A show significant negative effects of wealth on participation. The coefficient on counted assets is 100 times as large as the coefficient on equity in a home. Coefficients on each of the measures of predicted wages for husbands and wives, above and below the means, are negative and statistically significant. Participation responds nonlinearly to expected wages for the husband, but not for the wife. The number of minor children has a significant and large effect on participation. Disability of the householder increases participation significantly. Estimates of Model A are consistent with the two most similar studies of couples, those by Hagstrom (1991, table 8.1) and Martini (1992, p. 91). (Martini did not study asset-eligible nonparticipants as we do here.)

In general, the effect of incorporating information on response error into the probit for participation (Models B–E) is to increase the absolute magnitude of significant coefficients. The coefficients associated with wealth and expected earnings are especially affected, lending increased credence to the role of economic factors in the choice to participate. Coefficients on number of children and disabled householder imply that these factors also dramatically increase participation.

Although both Models B and C use a mean to predict response errors for households, the change in coefficients from Model A is not a proportional adjustment. For example, the largest difference between Model A and B occurs in the coefficient for counted assets, which nearly doubles. The coefficient on disabled head of household increases by .162, or 12%; the coefficient on number of minor children increases by .043, or 50%. The coefficient on home equity below \$75,000 decreases by −.034, or 30%, and the coefficient on wage of husband below the mean decreases by −0.013, or 9%. Because Model C uses scalar response error rates for married couples ($\tilde{p}$ = .008 and $\tilde{q}$ = .111) that are smaller than those in the remaining population, Model B overstates adjustment for response bias relative to Model C. As we discuss later, neither model captures the effect

Table 5. Sample Statistics of Predicted Response Errors in Primary Sample

Symbol	Used in	$\hat{p}_{4i}$ Mean	Standard deviation	$\hat{q}_{4i}$ Mean	Standard deviation
$\bar{p}$, $\bar{q}$	A	0	0	0	0
$\bar{p}$, $\bar{q}$	B	.0032	0	.1215	0
$\tilde{p}$, $\tilde{q}$	C	.0008	0	.1111	0
$\hat{p}(Z_{4i}^{(p)})$, $\hat{q}_{4i}(Z_{4i}^{(p)})$	D	.00736	.00881	.261	.195
$\hat{p}(Z_{4i}^{(p)})$, $\hat{q}_{4i}(Z_{4i}^{(p)})$	E*	.00736	.00881	.277	.200

* See text for explanation of imputations.

of distribution of propensity to errors in the population. Model B is shown to illustrate the fact that adjusting for probabilities of error from an aggregate benchmark may be far superior to no adjustment.

The most interesting use of the pseudolikelihood estimator is to impute the probabilities of response errors conditional on household characteristics. These results are shown in Table 7. Model D estimates the parameters $\hat{p}_{4i}$ and $\hat{q}_{4i}$ from probits based on per capita income, which is measured in both the primary sample and the validation sample and is known for nonparticipants. In Models D and E, estimates for the coefficients on counted assets, home equity, the poverty threshold, wage of the husband (below the mean), and presence of a disabled head of household are much larger than those for Models B and C (Table 6). The coefficient on counted assets is now $-.00246$—more than double the estimate for Model C and 2.4 times the "naive" probit that ignores response error, model A. The coefficient associated with home equity is $-.184 \times 10^{-4}$, 50% less than in Model C and 60% less than in Model A.

Model E uses $\hat{q}_{4i}$ from Model O2, which conditions on household per capita income, marital status, gender, and proxy interview status. The value of a more elaborate model is that income has a well-established correlation to family composition (Morgan 1974). The gender and proxy status of the person reporting receipt of food stamps is neither measurable nor logically defined for the nonparticipant population. It is necessary to impute these variables. Among participating couples, gender and proxy status of the reporter are strongly correlated; 13% of women and 44% of men are represented by proxy interviews. Reporters are 46% female. These proportions were incorporated into the imputation of proxy and gender. For this reason, estimates of Model E include variance associated with imputation errors.

The significant coefficients for Model E are slightly smaller than those for Model D, always less than 10% smaller, demonstrating that model D is not qualitatively different from Model E. This finding reflects the importance of income per capita in explaining response error. Intuition suggests that the reduction in the likelihood for Model E relative to Model D is the result of imputation error.

We tested the significance of differences between Models A and E; that is, the null hypothesis is $\beta_{\mathrm{A}} = \beta_{\mathrm{E}}$. The chi-squared test statistic (with 14 df) is 69.5, a finding that rejects the null hypothesis at all conventional significance levels. Testing that intercepts may differ but slopes do not, we reject the null hypothesis with a test statistic of 68.4. These tests are motivated by the assumption that Model E represents the correct, unbiased estimate of the coefficient vector β_f, whereas Model A represents estimates of probits that ignore response error. The difference $\hat{\beta}_{\mathrm{A}} - \hat{\beta}_{\mathrm{E}}$ estimates bias due to response errors. Bias for a mean correction for response error is given by $\hat{\beta}_{\mathrm{C}} - \hat{\beta}_{\mathrm{E}}$. Discussion

Table 6. Food Stamp Participation Models Corrected for Response Error

	Participation model: Scalar p,q		
Coefficient	*A: zeroes* $\bar{p} \equiv \bar{q} \equiv 0$	*B: means* $\bar{p}, \bar{q}$	*C: couple means* $\tilde{p}, \tilde{q}$
Intercept	1.476*	1.764*	1.638*
	(.354)	(.421)	(.392)
Wage of husband ≤ mean	−.140*	−.155*	−.142*
	(.0330)	(.0387)	(.0356)
Wage of husband > mean	−.0732*	−.0919*	−.0828*
	(.0218)	(.0282)	(.0252)
Wage of wife ≤ mean	−.205*	−.218*	−.221*
	(.0463)	(.0541)	(.0507)
Wage of wife > mean	−.191*	−.190	−.198*
	(.0893)	(.107)	(.0966)
Poverty threshold	.000286	.000375	.000329
	(.000196)	(.000225)	(.000213)
Number of minor children	.105*	.128*	.117*
	(.0369)	(.0433)	(.0408)
Other wealth ≤ \$75,000	-4.70×10^{-6}	-3.12×10^{-6}	-4.50×10^{-6}
	(4.59×10^{-6})	(5.26×10^{-6})	(4.91×10^{-6})
Other wealth > \$75,000	3.38×10^{7}	-3.54×10^{-7}	3.22×10^{-7}
	(5.42×10^{7})	(66.5×10^{-7})	(58.1×10^{-7})
Home equity ≤ \$75,000	$-1.13^{*} \times 10^{-5}$	$-1.48^{*} \times 10^{-5}$	$-1.26^{*} \times 10^{-5}$
	$(.291 \times 10^{-5})$	$(.412 \times 10^{-5})$	$(.354 \times 10^{-6})$
Home equity > \$75,000	8.77×10^{-7}	45×10^{-7}	17.3×10^{-7}
	(120×10^{-7})	(130×10^{-7})	(126×10^{-7})
Counted assets	−.00105*	−.00197*	−.00121*
	(.000149)	(.000351)	(.000261)
Disabled head	1.32*	1.48*	1.43*
	(.147)	(.195)	(.175)
Live in SMSA	.0848	.0751	.0838
	(.0899)	(.105)	(.0976)
Log-likelihood	−565.3	−563.9	−567.6

NOTE: Estimation using primary sample. Dependent variable = 1 if household reports Food Stamp Program participation. B, Mean reporting errors $\bar{p}, \bar{q}$ in the validation sample, C, Mean reporting errors for married couples.

* Indicates significance at the 5% level

Table 7. Food Stamp Participation Models Corrected for Response Error

	Participation model: Vector **p**,**q**	
Coefficient	D: C1, O1[a] $\hat{p}(Z_{4i}^{(p)}), \hat{q}(Z_{4i}^{(p)})$	E: C1, O2[a] $\hat{p}(Z_{4i}^{(p)}), \hat{q}(Z_{4i}^{(q)})$
Intercept	1.992[b]	1.932[b]
	(.467)	(.445)
Wage of husband ≤ mean	−.184[b]	−.184[b]
	(.0440)	(.0424)
Wage of husband > mean	−.0978[b]	−.0878[b]
	(.0309)	(.0288)
Wage of wife ≤ mean	−.201[b]	−.203[b]
	(.0598)	(.0573)
Wage of wife > mean	−.158	−.148
	(.127)	(.123)
Poverty threshold	.393	.384
	(.255)	(.244)
Number of minor children	.121[b]	.121[b]
	(.049)	(.047)
Other wealth ≤ $75,000	-2.25×10^{-6}	-2.025×10^{-6}
	(5.97×10^{-6})	(5.85×10^{-6})
Other wealth > $75,000	-11.2×10^{-7}	-9.72×10^{-7}
	(72.4×10^{-7})	(70.4×10^{-7})
Home equity ≤ $75,000	$-1.84^{b} \times 10^{-5}$	$-1.79^{b} \times 10^{-5}$
	$(.476 \times 10^{-5})$	$(.467 \times 10^{-5})$
Home equity > $75,000	113×10^{-7}	110×10^{-7}
	(135×10^{-7})	(134×10^{-7})
Counted assets	−.00246[b]	−.00248[b]
	(.000519)	(.000532)
Disabled head	1.58[b]	1.51[b]
	(.212)	(.196)
Live in SMSA	.071	.069
	(.121)	(.117)
Log-likelihood	−516.9	−522.8

NOTE: Estimation using primary sample. Dependent variable = 1 if household reports Food Stamp Program participation.
[a] See Tables 3 and 4.
[b] Indicates significance at the 5% level.

of Models C–E demonstrates that the mean correction is not adequate.

Table 8 displays the density of predicted participation for each model. The principal effect of adjusting for response error is to increase the proportion of the primary sample at the extremes; the reduction in the probability of participation estimated for households with a probability of participation less than .2 is especially noteworthy. Model E differentiates more sharply between the nonparticipating asset-eligible households and persons with a moderate likelihood of being a participant than Model A. A second illustration of the differences among the models is shown in Table 9. The probability of participating in the Food Stamp program falls much more rapidly as home equity increases under Model E than it does under Model A. Tabulation of predicted Food Stamp participation by predicted wage rates for husbands shows that Model E concentrates the probability of participation on low-wage workers to a greater extent than Model A.

From a policy perspective, the bias in the coefficient of counted assets is critical. If all else is held equal, then the change in probability of participating in Food Stamps with a change of 1 dollar in counted assets is 2.3 times higher (in absolute value) under model E than under Model A.

Table 8. Distribution of Predicted Food Stamp Participation (N = 2,624)

	Model				
Decile	A	B	C	D	E
			Distribution by percentile, first decile		
0.0	781	1,035	811	1,139	1,179
0.1	233	161	221	177	188
0.2	193	157	174	130	132
0.3	134	103	117	98	99
0.4	120	94	111	87	84
0.5	98	81	94	72	67
0.6	102	70	84	53	50
0.7	83	56	78	43	53
0.8	54	51	71	41	52
0.9	75	47	45	52	41
			Distribution by decile		
1	1,873	1,855	1,806	1,892	1,945
2	375	328	377	301	283
3	159	158	172	147	150
4	87	102	97	105	91
5	31	60	56	59	44
6	21	29	24	25	21
7	23	17	23	18	18
8	16	23	24	21	21
9	18	18	13	18	18
10	21	34	32	38	33

5. CONCLUSIONS

Response errors cannot be treated as random in modeling primary data on Food Stamp program participation in 1984. Furthermore, this investigation suggests that at least some of the errors are not simply "forgetfulness," but rather represent purposeful misrepresentation. Simple forgetfulness should not be related to income and should be positively related to proxy interviews. Estimates of participation demonstrate that predictions made from probit models that do not incorporate response errors will be incorrect even for modest levels of response error.

This work goes beyond that of Marquis and Moore (1990), who attempted to isolate cognitive forces that generate response error. We used repeated measures, designed into the *Survey of Income and Program Participation* panel,

Table 9. Predicted Food Stamp Participation by Level of House Equity

	Home Equity					
Model	Not owner	Under $10,000	$10,000–$30,000	$30,000–$50,000	Over $50,000	All
A	.145	.101	.061	.045	.018	.099
	(.195)	(.137)	(.107)	(.101)	(.045)	(.161)
B	.160	.109	.060	.043	.015	.106
	(.221)	(.161)	(.126)	(.111)	(.046)	(.183)
C	.160	.112	.066	.048	.019	.109
	(.211)	(.153)	(.119)	(.110)	(.050)	(.175)
D	.158	.105	.054	.035	.011	.103
	(.226)	(.162)	(.117)	(.104)	(.037)	(.185)
E	.146	.096	.049	.033	.010	.095
	(.218)	(.153)	(.111)	(.100)	(.034)	(.177)
N	1,194	341	514	309	266	2,624

NOTE: Cell means with standard deviations in parentheses.

to predict error rates for a primary sample that contains more households and is collected at a different time than the measures of response errors. We showed that personal and household characteristics that have relatively small correlations to the probability of response errors may create large differences in the estimates of probits modeling decisions by households.

The small sample of data on which errors of omission are modeled does not give great confidence in the substantial bias that we have demonstrated. Nonetheless, our estimates support those of Ferber et al. (1969a,b) and Morgenstern (1963) in their concern for calibrating survey data with models of response error. Validation samples clearly need to be replicated.

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