SAMPLE ATTRITION AND RESPONSE ERROR: DO TWO WRONGS MAKE A RIGHT?

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ABSTRACT

Two important issues in the SIPP data are attrition and measurement error. Both of these issues have been previously studied (e.g. Marquis and Moore (1990); Bollinger and David (1993a,b); David (1989) and Zabel (1995)). However, the relationship between measurement error and sample attrition has not been previously studied. The work here examines the relationship between incidence of reporting error and incidence of sample attrition. We extend the work of Bollinger and David (1993b) by adding a variable representing the response pattern of the family unit in waves three through eight to a Probit model of reporting error for food stamp participation in the first wave. We find a strong and stable relationship between reporting error and non-response. The results support the "cooperator / non-cooperator" hypothesis and suggest that a latent variable is common to both reporting error and non-response. Further research is proposed.

KEYWORDS

Response Error, Sample Attrition, Food Stamp Participation

1. THE PROBLEM

In 1992 we began to research socio-economic factors associated with response error (Bollinger and David 1993b). We were aided in this effort by Kent Marquis and Jeff Moore who generously gave us access to data on errors obtained by comparing administrative data to survey reports. Our initial findings indicated significant and important relationships between income and errors in reporting participation in the Food Stamps Program. We also determined that proxy interviews were at least as accurate as self-reported interviews. One intuition behind the findings was that some respondents are cooperative (good reporters) and a few are uncooperative (bad reporters). Those initial findings pose two extremely important questions: A. Are the findings robust? B. Could it be that uncooperative respondents disappear from panels, leading to a partial correction for error observed in early waves? This paper is the outcome of early efforts to establish robustness and determine the bounds on estimates of models from panel data that include a combination of non-response and response error.

The execution of panel surveys results in non-response and response errors. Those errors imply a mean square error including error variance and bias terms. Current research about that error variance is sharply focused on either non-response or on response error. This paper investigates the possibility that a common cause may induce both response error and non-response. We investigate that hypothesis on the *1984 Survey of Income and Program Participation (SIPP)* whose design entails eight (or nine) interviews from sampled individuals over a period of 32 months.

The larger context for this work is estimation of models that describe economic behavior from survey observations. Non-response distorts estimates of models when censoring rates vary in dimensions that are not controlled in the model specification. Response error introduces noise into both independent and dependent variables. That noise masks underlying behavior (biassing parameters) and reduces the power of tests of the significance of parameters.

1.1 Non-response

Non-response includes coverage or unit non-response; partial response, consisting of interviews in some waves and wave non-interview; and item non-response. Effort to compensate for unit non-response focuses on weighting (though imputation is done in the Census for households where no one can be contacted). Effort to compensate for item non-response focuses on imputation. Modeling the selectivity of the responding population compensates for partial response. Generally weighting and subsequent analysis of the responses assumes that non-response is ignorable, *i.e.* distributed at random within some space determined by variables unrelated to the behaviors producing non-response. (For an exception see Lillard *et al.* 1986.)

Sample survey professionals agree that appropriate effort – callbacks, conversion of refusals, and extending the close-out date for response – can increase response, albeit at increased cost (Groves 1989, Dillman 1978). Execution of sample surveys has stressed contact with each sampled element. Budget and time constraints imply compromises between such effort and minimizing the mean square error of the data collected.

In field work, failure to contact individuals is clearly differentiated from refusals that represent unwillingness to cooperate. Good interviewing practice demonstrates that some refusals can be "converted" to responses, because interviewers vary in their ability to motivate cooperation and because the circumstances of respondents vary over time. Nonetheless, most organizations limit their attempts to convert refusals. In panels, rules limit efforts to contact refusals in subsequent waves of interviewing. In the SIPP, refusals that are not associated with an obvious temporary problem (family emergency, etc.) are not followed, resulting in censoring of the remaining data collection.

1.2 Response Error

Incorrect responses clearly contribute to the mean square error of observations. Where incorrect responses have systematic components, they can seriously bias inferences from the data. Little is known about how to reduce response error, because field procedures are seldom validated against objective data, particularly in the realm of economic attributes and behaviors of individuals and organizations. A concerted effort by Ferber (1966) and Lansing (*et al.* 1961) revealed much of what we know about reducing error in the reporting of assets and debts and afforded thinking about the mechanisms that induced response errors (Maynes 1965). (The Census Bureau regularly matches *Current Population Surveys* and SIPP to Federal income tax records, but that comparison is flawed by conceptual differences in the reporting unit and the amounts elicited which makes validation difficult.)

Around 1964, Ferber proposed survey designs that coordinated list and area samples to provide "calibration functions" for data needed to estimate savings. Marquis and Moore (1990) realized Ferber's design in their collection of data to validate reports of transfer income received by persons in the SIPP sample. We pursued estimation of "calibration functions" describing response errors in reports of Food Stamp recipiency in Bollinger and David (1993a). Our approach was to explain measurement error by parametric models; estimates of those models were then incorporated into the estimation of behavioral models from sample surveys. That idea is parallel to the idea of adjusting models for selection introduced by Heckman (1979) and widely used in econometric modeling since. Non-parametric approaches to this problem are explored in Manski (1989).

1.3 Macro Comparisons

Orders of magnitude for the cumulative effect of coverage, non-response, and response errors can be estimated by comparing aggregates from two or more independent sources of information. We term such comparisons "macro comparisons" because they identify differences in the population as a whole or in population sub-groups and reflect only net errors. Vaughn (1989) provides comparisons for the 1984 SIPP. His work has been updated by Coder and Scoon-Rogers (1994).

Aggregate comparisons net out over-reporting and under-reporting by different individuals. They also fail to identify differential measurement errors in sub-populations that affect estimates of responses to attributes of the respondent.

2. SPECIAL FEATURES OF THE FOOD STAMP PROGRAM

Food Stamps are the most universal assistance program, providing benefits to about 7.4 million households in 1992 (Ways & Means 1994). Benefits take the form of coupons that may be redeemed for food items at retail outlets. The coupons tangibly manifest the benefit. They are regularly used by the recipient household, so they are easily distinguished from other aid which comes in less visible payments, possibly deposited directly to a checking account. Coupons minimize respondent confusion about the source of the benefit. (Just under half of Food Stamp households receive AFDC and about a quarter receive SSI or Social Security.)

The law requires that income of all household members be considered in determining eligibility, except in unusual circumstances (separate cooking facilities for unrelated household members). The eligibility rule implies that the household is the logical unit for analysis (Martini 1992). This fact motivates our analyses of error at the household level.

3. A COGNITIVE PARADIGM FOR RESPONSE AND NON-RESPONSE

Eisenhower, Mathieowetz, & Morganstein (1991) relate cognitive research on responses to recall error in surveys. The response errors of primary interest to this research relate to "judgement" by the respondent to supply sensitive information and the "saliency" of the type of income received. Bradburn and Sudman's (1974) review of earlier literature on response error highlights judgement as it relates to threatening questions. Correct information that reduces self-esteem or imposes penalties, creates a threat. Threat increases response errors. Threat may be different across genders and income levels. Saliency is crucial also. The ability of individuals to recall the income source varies across sources. Due to the coupon utilization in FS, it seems that forgetting should not be a major source for this program. Those ideas can be quantified and modeled in relation to program participation.

4. DATA SOURCES AND DEFINITIONS

The SIPP represents the noninstitutional population of the United States. The 1984 panel encompasses approximately 20,000 households. Each household is interviewed eight (or nine) times. Each interview period, called a wave, elicits responses about individual and household activities during the previous four months.

In every wave, each adult member of the family was asked whether s/he was the authorized recipient of food stamps in any of the preceding four months. Respondents answering "yes" to this screening quest ion were then queried about recipiency and payments received in each of those four months.

The validation sample used here is obtained by matching administrative records from Florida, Pennsylvania and Wisconsin to waves 1 and 2 of the 1984 SIPP panel. The three states chosen for validation study were selected primarily for the willingness of state agencies to release accurate, machine readable, and identifiable individual level data to the Census Bureau. The time window covered by the validation sample is June 1983 through May 1984. Analysis that follows focuses on responses to the screening question for wave 1.

Validating data were matched to the wave 1 and 2 SIPP data by Social Security Number, name, house number, street name, apartment number, city, zip code, gender and date of birth. Administrative records for an individual exist only if that individual was a participant in the Food Stamp program sometime during the 12-month period from June 1983 through May 1984. If administrative records do exist, then the exact participation data is available. If administrative records do not exist, then the maintained assumption is that the individual did not participate in the Food Stamp program at all during the first two waves of the SIPP. This assumption rules out possible problems with the administrative records and with the Census matching which are discussed in previous work (Bollinger and David, 1993a). Error in the administrative records and matching are second-order in relation to the reporting errors analyzed here.

4.1 Attrition and Other Interview Non-Response in the SIPP

The terms used to describe response and non-response patterns are used in several ways. Table **??** gives definitions used here with appropriate examples. McArthur (1987) pointed out that some persons are randomly unavailable for interview, so that a terminal non-interview is insufficient to identify attrition. That makes it useful to focus on cases of two missing interviews prior to termination as identifying attrition. The gap response pattern makes it clear that some persons may be initially difficult to contact and attrit later. When continuous data are required for estimation, gap response provides no usable information after the first gap.

Table **??** shows the attrition patterns reported by Zabel (1995), modified to include an estimate of persons missed as the consequence of unit non-response. The table includes only those persons who were to be followed for eight (or nine) waves. Others were censored. Table ?? offers a different perspective. It includes persons followed after wave 1 and eligible for interview, that is over 14 years of age. Three statistics stand out in the Table: 0.031 of all persons are inadmissable for our analysis because they gave only the first interview. Furthermore, the patterns that include missing one or two interviews without attrition are of the same order of magnitude as attrition after the second wave (0.086 under other patterns, compared to 0.095 under dense attrition). We can not ascertain what proportion of other patterns are admissible for the response error analysis.

Our measures of non-response deal with the third to eighth (ninth) interview. Therefore they describe behavior subsequent to the two interviews used in constructing the validation data. It is not important to our analysis that members of the household at wave 1 may no longer live together at later points in time. It is important to understand that any estimation utilizing data from later waves is conditional upon the response pattern. That is, estimation of participation in the FS program from wave 4 data is conditional upon participation in the survey in wave 4. As we shall see below, individuals who fail to participate in one wave are likely to fail to participate in other waves.

4.2 Non-Response, Censoring, and Out-of-Scope

The 1984 SIPP panel is designed to follow all adults residing in households sampled for the first wave of interviewing. We differentiate between three types of non-response: non-response due to sample design, non-response due to changes in the universe, and non-response due to behavior.

Five aspects of the sampling design introduced censoring:

- Non-respondents to the first interview were not incorporated into later waves (because of the difficulty of knowing that each person in such households was at risk for an interview in the first wave).
- 18% of sampled individuals were deleted from the sample at waves 5 and 6.
- Only 25% of the remaining persons were interviewed for a ninth contact.
- Persons who could not be contacted by phone after moving more than 100 miles from a Census sampling unit were not followed.
- Children who moved into households that did not include either parent were not followed. Such children could become eligible for interviewing when they reach age 15.

The universe of the study was individuals living within the continental United States. During the survey period, some individuals died or moved out of the continental US. Both place the individual out-of-scope for measurement.

Individuals at risk of being interviewed may not respond. Refusal of the members of the household or the entire household to respond at some wave reveals non-cooperativeness. Cases where the sampled persons changed residence and Census was not able to find the new residence also may indicate non-cooperativeness. (Cases where the new address was located but Census chose not to follow are out-of-scope.)

Cases of “temporary absence” and “no one home” do not clearly indicate non-cooperativeness. However, we classify these categories as behavioral non-response. Although some families will not be contacted in some waves due to normal family events, we argue that failure to respond for any behavioral reason may signify an unwillingness to cooperate with the survey.

The behavioral category is the focus of this research. We hypothesize: Decisions by family members that result in behavioral non-response result from unwillingness to cooperate. The level of cooperation is linked also to the accuracy of the response.

Dense attrition, gap attrition and other non-response patterns are summarized for each individual, using indicator variables and a more continuous measure of cumulative non-response. Non-interview information classifies response status of each individual in each wave in to 25 categories. We partition these categories into two groups. One group contains the behavioral non-response; the other group contains response and non-response due to sample design or change in the universe. Each individual was classified into one of these two groups for each wave. We refer to those in the non-response due to behavior group as "missed interviews". A narrower definition of behavioral non-response would include only those who were classified as type-Z refusals, or cases where the entire household refused an interview. We also consider this narrower measure.

4.3 Aggregation of Non-Response Into Households

One further difficulty must be solved before errors in reporting Food Stamp recipiency can be related to patterns of non-interviews. The Food Stamp program applies to households (except in rare instances). Bollinger and David (1993a) report that inconsistencies in identifying the certified individual who receives Food Stamps lead to two offsetting errors and correct reporting of recipiency for the household aggregate. The household's non-response behavior must be summarized to model error at the household level. No particular aggregation function appears logically superior. If no household members can be interviewed, individual and household status will be identical. If some individuals can be interviewed and others can not, is the household more like one that can not be contacted or more like an interviewed household?

Eight measures of household non-response were constructed from the individuals who were members of the household at wave 1. **Anymis** indicates that at least one adult missed at least one interview during waves 3 through 9. **Fammis** indicates that all adults in the family missed at least one particular wave (*e.g.*, the entire household had no response due to behavior for wave 4). **Famref** indicates that the household refused at least one interview. **Pctmis** measures the percentage of possible interviews that were missed by the family members. Formally it is the number of missed interviews divided by the number of possible interviews (for a family with two adults who were within scope for waves 3 through 9, the number of possible interviews is 2 persons $\times$ 7 waves = 14). **AnyZ** indicates that at least one family member was classified as a type Z non-interview. **Twomis** indicates that at least one family member missed at least two interviews. **Fammis2** indicates that the whole family missed at least two interviews. **TwoZ** indicates that at least one family member was classified as a type Z non-interview at least twice.

Table **??** displays sample counts for the 7 categorical variables. As can be seen, of the 66 families with Anymis = 1, 45 (68%) also have Twomis = 1. Similarly, of the 42 families with Fammis = 1, 30 families (71%) had Fammis2 = 1. It is interesting also that of the 66 families with Anymis = 1, 42 (64%) of them have Fammis = 1. Thus when anyone in the family misses an interview, there is a high probability that all members will miss an interview. The AnyZ and TwoZ variables capture so few families that they are not of any real interest. The same is true of Famref. The variable Pctmis, shown in Table **??**, is interesting because of its bimodal distribution. The primary mode is at Pctmis = 0. However, a secondary mode occurs in the 0.1 to 0.2 range.

In our previous work, we found that errors in reporting FS were concentrated at the screening question level. That is, failure to report FS participation for a given month was often (about 91% of the time) associated with failure to report participation for the entire wave. (Participation occurred in multiple months for many participants.) Hence ,here we focus upon participation in FS as measured by the screening question. Table **??**, row 1, gives the rates of omission for FS. An error of omission occurs if the family fails to report participation in FS for any month in the wave, given that they did participate for some month. Errors of commission in FS are very uncommon (only 5 in this sample). As in our previous work, there is a relationship between errors of commission and income. We believe this relationship is largely definitional; hence we focus on the relationship between non-response and errors of omission in FS. Some, but not all, errors which occur due to "timing" are avoided by analyzing the screening question.

4.4 Household Measures of Response Error

Tables **??** and **??** give tabulations of FS errors and the Anymis and Fammis variables. As can be seen in Table **??**, nearly 23% of the families who have any member miss at least one interview, fail to correctly report FS participation. This compares with only 14% in the whole sample. A standard test for differences between the two populations reveals a test statistic of 2.278, which is significant at the 5% level. A similar analysis for the Fammis variable yields a similar conclusion. While this is of use and interest, since it is known that both reporting error and non-response in the SIPP are related to income, gender and marital status, one must ensure that the apparent relationship between response error and non-response is not spurious. This question is examined in the next section.

5. ESTIMATION OF DESCRIPTIVE MODELS

Ideally, one would estimate structural models of reporting error. Structural models are those which not only relate reporting error to various correlates, but also identify causal relationships. Structural models would allow surveys to be better-designed. The descriptive models estimated here provide a rough scaffolding for later research that will explore alternative structural models. In particular, they help to understand whether earlier results are independent of non-response behavior or whether they act as a proxy for an omitted non-response variable. Descriptive models also allow us to dismiss non-response as a consideration in structural modeling should it prove to be unrelated to response error.

In previous research we forwarded plausible arguments leading to the hypotheses that reporting errors in the SIPP are related to gender of the respondent or head of household, age, race, marital status and income. We found that income was robustly related to reporting error for the month prior to the interview. Gender and marital status were less robustly related to error. We use the prior models as a starting point. Table **??** gives estimates of the Bollinger & David (1993b) models on the screening question. Two models are presented. Model one includes only Percinc, family per capita income (total family income/number of family members - measured in wave 1 month prior to interview). Model two adds marital status, gender, an interaction between marital status and gender, and an indicator for self report to Model one.

Table **??** gives results for Model 1 when measures of non-response are added to Model 1. Table **??** gives results when non-response measures are added to Model 2. One of the most striking aspects of the results is the stability of the other parameters when the non-response variables are added. Clearly, there is little change in the coefficients in either Model 1 or Model 2. The income effect and the non-response effect are relatively orthogonal.

A latent (unobservable) variable which causes both reporting error and non-response could be the source of this finding. Obviously, non-response behavior subsequent to the time period covered by the validation sample can not cause the errors of omission observed in wave 1.

No measure of non-response seems to dominate. The five measures all seem to work equally well, quantitatively and qualitatively. Of course, the measures are highly related. Table **??** gives the coefficients of the first principal component for two sets of non-response measures. The full analysis includes all eight measures of non-response, while the partial analysis considers Anymis, Twomis, Fammis, Fammis2, and Pctmis. No one variable can be said to capture most or all of the variance in all variables. The variables Famref, AnyZ and TwoZ are less heavily weighted than the remaining non-response measures. Other analysis (not presented here) confirms the lack of importance of those measures. This motivates the partial analysis. Note that the five included measures of non-response have almost identical weights.

Table **??** gives four more estimates of the model of FS error. The variable PrinF is the principal component from the full component model (first column of table **??**); the variable PrinP is the principal component from the partial model (second column of table **??**). The important conclusion we draw from the results presented in table **??** is that any of the five measures of the non-response captures the latent variable common to response error. No one measure is superior.

We also examined errors of omission in AFDC. As noted in Marquis and Moore (1990), AFDC has a high rate of net error. We also find little relationship between AFDC errors and other demographic and economic variables. Preliminary results will not be presented here but they do not match the results we have in the food stamp population. In fact, there appears to be no relationship between errors in reporting AFDC and income, gender, marital status or measures of non-response in the partial analysis undertaken. Coefficients were unstable across specifications and had very large standard errors. One reason may be the small sample size; only about 100 AFDC participants are available. However, we hypothesize that the primary problem is that program confusion confounds misreporting of AFDC. Past work (Vaughn, Whiteman, and Lininger, 1984) confirms confusion of AFDC with general welfare. Confusion implies that response error models needed to understand AFDC must be more complex than those presented here.

6. CONCLUSIONS AND FURTHER RESEARCH

Panel data afford two opportunities not economically available to *ad hoc* surveys. The extended period of data collection makes it economic to coordinate and integrate survey data with administrative data. Secondly, the continuing contacts with respondents elicit conditioned responses that may be more accurate. We have demonstrated that for at least one major program supporting impoverished families, those units who continue to give interviews are less error-prone. Thus loss of sample through attrition affects both the level of response error and the coverage of the remaining observations.

We have found that non-response does not proxy for income effects that we modeled in 1993. It provides significant additional explanation of response error. The existence of this systematic variation in response error must be confirmed in replications of the Marquis and Moore validation sample. Two hundred cases are not sufficient to provide the precision in calibrating survey model estimates that is required for good policy-making.

In the future, we will be able to improve on these estimates because of our continuing collaboration with the Bureau of the Census. The results presented today exclude validation data from New York state which may be added to the sample being analyzed. The results can be extended by analyzing other programs that have been validated using a more complex model of errors that encompasses both program confusion and errors of omission. Lastly, the results can be analyzed across two waves of interviewing to provide understanding of the extent to which poor reporting is indeed specific to individuals or to the sequence of interviews and interviewers.

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TABLES

TABLE 1

Definitions of Response and Non-Response

Categories	Example Pattern	Characteristic
Unit Non-Response	0 0 0 0 0 0 0 0 0	No Interviews
Complete Response	1 1 1 1 1 1 1 1 1	All Interviews
Attrition		
Dense Response	1 0 0 0 0 0 0 0 0	Attrition at Second Interview
	1 1 1 0 0 0 0 0 0	Attrition at Fourth Interview
	1 1 1 1 1 1 1 0 0	Last Two Responses Missing
Gap Response	1 1 0 1 0 0 0 0 0	Missed Interview Prior to Attrition
Other Non-Response	1 1 0 1 0 1 1 0 1	Interview in Last Wave

TABLE 2

Attrition in the 1984 SIPP (at risk for 32 months)

Wave	Sample	Count	Probability
0	46037	2256	0.049*
1	43781	2572	0.0587
2	41209	2512	0.0610
3	38697	2100	0.0543
4	36597	1761	0.0481
5	34836	1514	0.0435
6	33322	1240	0.0372
7	32082	828	0.0258
8	31254		

*Estimated from type A non-response, unadjusted
Modified from Zabel (1994)

Table 3

Exits of Panel Persons
(Individuals over 14 and to be interviewed wave 1)

Description	Probability	Subtotal
Complete	0.67	
Partial		
Out of Scope (oos)	0.032	
Other	0.002	0.704
Incomplete		
Attrition, Dense		
1111 1100	0.012	
1111 1000	0.015	
1111 0000	0.020	
1110 0000	0.022	
1100 0000	0.026	0.095
Inadmissable		
1000 0000	0.031	
Other Patterns*		
1 missing	0.057	
2 missing	0.029	
missing and oos	0.003	
other	0.033	
Wave 1 Respondents	0.952	
Non-respondents	0.049	
Total	1	

* Potentially indamissable due to missing second wave.

Table 4

Descriptive Statistics of Categorical Measures of Non-Response
Food Stamp List Sample, N = 201

Variable	Anymis	Fammis	Twomis	Fammis2	AnyZ	TwoZ	Famref
= 0	135	159	156	171	191	197	184
= 1	66	42	45	30	10	4	17

Table 5

Descriptive Statistics for Pctmis
Food Stamp List Sample

Value Range	Number
0	135
0< - 0.1	9
0.1< - 0.2	17
0.2< - 0.3	11
0.3< - 0.4	3
0.4< - 0.5	8
0.5< - 0.75	7
0.75< - <1	9
1	2

Table 6

Food Stamp List Sample
Tabulation of FSerr and Anymis

	Anymis=1	Anymis=0
FSerr=1 (Coll. %)	15 (22.7)	13 (9.6)
FSerr=0 (Coll. %)	51 (77.3)	122 (90.4)

Table 7

Food Stamp List Sample
Tabulation of FSerr and Fammis

	Fammis=1	Fammis=0
FSerr=1 (Col. %)	10 (23.8)	18 (11.3)
FSerr=0 (Col. %)	32 (76.2)	141 (88.7)

Table 8

Reporting Errors in FS

Administrative Record	SIPP Report	
	FS = 1	FS = 0
FS = 1	173	28
FS = 0	5	2300

Food Stamp List Sample is first row

Table 9

Basic Models: Food Stamp List Sample
Dependent Variable: FSerr

Variable	Model 1	Model 2
Intercept	-1.323 *	-0.408
	(0.156)	(0.703)
Percinc (000's)	0.696*	0.810*
	(0.328)	(0.338)
Gender		-0.829 *
		(0.343)
Marital Status		-1.308
		(0.971)
Marital Status*Gender		0.830
		(0.550)
Self		0.549
		(0.393)
Log Likelihood	-77.11	-73.26

* Indicates significance at the 5% level
† Indicates significance at the 10% level

Table 10

Model 1 With A Single Measure of Non-Response
Dependent Variable: FSerr

Variable	Model 1A Anymis	Model 1B Fammis	Model 1C Pctmis	Model 1D Twomis	Model 1E Fammis2
Intercept	-1.513 *	-1.499*	-1.459*	-1.450*	-1.414*
	(0.185)	(0.181)	(0.174)	(0.176)	(0.169)
Percinc (000's)	0.670*	0.772*	0.695*	0.702*	0.711*
	(0.329)	(0.333)	(0.333)	(0.332)	(0.331)
Non-Response	0.506*	0.584*	0.886*	0.464†	0.473†
	(0.232)	(0.256)	(0.412)	(0.251)	(0.286)
Log likelihood	-74.74	-74.57	-74.87	-75.44	-75.79

Table 11

Model 2 With A Single Measure of Non-Response
Dependent Variable: FSerr

Variable	Model 2A Anymis	Model 2B Fammis	Model 2C Pctmis	Model 2D Twomis	Model 2E Fammis2
Inter.	-0.775	-0.625	-0.620	-0.670	-0.535
	(0.716)	(0.713)	(0.708)	(0.718)	(0.708)
Percinc (000's)	0.786*	0.873*	0.801*	0.817*	0.816*
	(0.339)	(0.343)	(0.342)	(0.341)	(0.340)
Gender	-0.766 *	-0.768*	-0.769*	-0.792 *	−0.791*
	(0.344)	(0.346)	(0.344)	(0.344)	(0.344)
MS	-1.161	-1.266	-1.401	-1.265	-1.304
	(0.989)	(0.990)	(0.990)	(0.987)	(0.985)
MS*Gender	0.752	0.822	0.883	0.797	0.829
	(0.558)	(0.558)	(0.562)	(0.557)	(0.556)
Self	0.614	0.480	0.527	0.622	0.524
	(0.399)	(0.393)	(0.392)	(0.401)	(0.391)
Non-Response	0.492*	0.526*	0.819†	0.468†	0.419
	(0.239)	(0.261)	(0.422)	(0.257)	(0.291)
Log Likelihood	-71.15	-71.29	-71.44	-71.64	-72.27

Table 12

Principal Components of
Non-Response Measures

Variable	Full	Partial
Anymis	0.399	0.425
Fammis	0.412	0.443
Famref	0.318	
Pctmis	0.437	0.470
Twomis	0.414	0.442
Fammis2	0.419	0.454
AnyZ	0.139	
TwoZ	0.110	
Eigenvalue	4.511	4.023

Table 13

Models with Principal Components
Dependent Variable: FSerr

Variable	Model 1F	Model 1G	Model 2F	Model 2G
Intercept	-1.352*	-1.359	-0.551	-0.559
	(0.160)	(0.161)	(0.704)	(0.704)
Percinc (000's)	0.705*	0.715	0.810*	0.822*
	(0.331)	(0.332)	(0.340)	(0.341)
Gender			-0.763	-0.767*
			(0.345)	(0.345)
MS			-1.291	−1.280
			(0.994)	(0.993)
MS*Gender			0.819	0.817
			(0.560)	(0.560)
Self			0.546	0.550
			(0.393)	(0.394)
PrinF	0.102*		0.093†	
	(0.049)		(0.050)	
PrinP		0.117*		0.109*
		(0.052)		(0.053)
Log Likelihood	-75.00	-74.63	-71.61	-71.19