INVESTIGATION OF GROSS CHANGES IN INCOME RECIPIENCY FROM THE SURVEY OF INCOME AND PROGRAM PARTICIPATION

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INTRODUCTION

The Survey of Income and Program Participation (SIPP) is a longitudinal survey of households that collects economic information about the U.S. population. For two and one-half years the members of a household are interviewed at four month intervals and information is obtained for each of the four months preceding an interview. (This four month period is also called a "wave.") One type of estimate that can be derived from this monthly data is that of the number of people who change their response to a question between consecutive months or between any two fixed time points. A previous study (Burkhead and Coder, 1985) examined month-to-month changes in receipt of five different income types and two noncash benefits. It showed that, for the first twelve months of SIPP, the number of reported changes in recipiency status between the last month of one interview period and the first month of the next interview period was far greater than the number reported between any two months of the same interview period. Burkhead and Coder discussed these differences in relationship to questionnaire wording/design and respondent recall error.

In this investigation we are looking for more direct causes of the discrepancy in the between/within interview numbers of gross changes. (A gross change between two times is the number of people in state A at the first time and state B at the second time. The distributions of gross changes refers to these numbers for a specified set of pairs of states. We will be looking at reported gross changes only.) There are three phases of this investigation.

1. Empirical analysis of data to determine if demographic characteristics of individuals are related to the discrepancy.
2. Description and estimation of models for the effect of time in sample, recall lag and other sources of response error on reported gross changes.
3. Estimation of response error from outside sources and use of it in conjunction with the models.

Here we will present an empirical analysis and examine any significant results. Two models for relating error sources to gross changes are then proposed and presented for use in the next phase of investigation.

EMPIRICAL ANALYSIS

The goal of empirical analysis is to use simple methods to detect the existence of obvious relationships between demographic/interview characteristics and changes in receipt status of seven income types and food stamps. There are four receipt states for two consecutive months: RR, RN, NR and NN, where R = receipt and N = nonreceipt. The income types of interest are social security, unemployment compensation, private pensions, VA compensations and pensions, supplemental security income, child support and AFDC. They will be examined with respect to age, sex, race, marital status, education, relationship to principal person, household size, tenure, SMSA size and interview status. The distribution of gross changes in receipt status between consecutive months for each income type will be computed with respect to all pairs of demographic characteristics. This will produce 360 sets of distributions for examination. Any apparent relationships may suggest other distributions for examination.

The categories used for demographic variables are defined as follows.

age: 15-30, 31-45, 46-60, 61+
sex: male, female
race: white, nonwhite
education: elementary, high school, above high school
marital status: married, (separated, divorced, widowed), never married

household size: 1,2,3,4-5,6+
tenure: home owned, not owned
relationship to reference person: reference person, spouse, child, other
SMSA size: not in an SMSA, 1 million +, less than 1 million
interview status for consecutive months: SS,SP,PS,PP where S=self, P=proxy

The file of monthly data was created from the first four waves of data available for each household. Each of these waves is searched for all persons who reported receipt of any of the income types of interest during any month of the wave. For each such person all the information available for the 16 month period is collected and placed on a record. This record will then be used if the person was interviewed for each of the four waves. (Restricting the analysis to these persons follows the Burkhead and Coder data set selection for the first twelve months.) A wave on the record was then used only if it was preceded by a wave of matching data. This ensures that the last three months of a wave are used in the calculations only if the first month is also. (An important fact to remember is that the large majority of people are not included on this file because they do not receive any of these income types.)

How will we determine if any relationships exist? When the monthly gross changes are computed there are usually two to five times as many RN and NR reported for the first month of a wave as there are for the other three months. (See Table 1.) For any pair of demographic variables to be a determinant of this change, we would have to observe a huge difference in the number of RN and NR reported in the first months of waves as compared to the last three months for some combination(s) of these variables, but not for others. We will be looking for one or more combinations to exhibit this behavior.

As a theoretical example of the distributions that were calculated see Table 2. There are two such tables for each comparison. The first is for all first months of a wave combined (between waves) and the second is for all months two, three, and four combined (within waves). This means that the total number of observations in the second table is three times the number of observations in the first.

TABLE 2

		RACE: white		RACE: non-white	
SEX	male	P_1RR P_1NR	P_1RN P_1NN	P_2RR P_2NR	P_2RN P_2NN
SEX	female	P_3RR P_3NR	P_3RN P_3NN	P_4RR P_4NR	P_4RN P_4NN

Within each cell defined by a particular combination of demographic characteristics we calculate the probability of each receipt state, $P_iAB=P$ (receipt state AB/cell i). Let P_iAB_w denote such a probability within waves and P_iAB_b the corresponding between wave probability. Compare P_iNR and P_iRN for between waves to those for within wave. If this demographic combination has no relationship to gross changes, the ratios P_iNR_b/P_iNR_w should be fairly constant for i, as should the ratios P_iRN_b/P_iRN_w. If one and/or both of these sets of ratios differ "greatly" between cells, this indicates the type of relationship we are looking for. (It is important to note that no statistical tests were performed. Comparisons are made by examining distributions for specified types of "noticeable" differences.)

When examining interview status the situation is somewhat different because two of the interview status pairs, PS and SP, cannot occur within waves. In this case we look for large differences in the distributions of P_iNR_b and P_iRN_b between cells.

Examination of these tables showed no major relationships between demographic variables and the gross changes. Some small differences in distributions occur, but nothing on the order of magnitude of the between/within wave gross change differences. As an example, see Table 3, sex x race for food stamps.

TABLE 3.A

Food Stamps: Between Waves
Race x Sex

Race	Sex	RR	RN	NR	NN
white	male	44.3 (547)	11.8 (146)	6.1 (75)	37.9 (468)
	female	59.7 (1560)	7.8 (205)	6.2 (163)	26.2 (684)
non-white	male	54.0 (262)	10.3 (50)	7.6 (37)	28.0 (136)
	female	68.9 (1086)	6.2 (97)	4.7 (74)	20.3 (320)

TABLE 3.B

Food Stamps: Within Waves
Race x Sex

Race	Sex	RR	RN	NR	NN
white	male	49.3 (1830)	2.0 (73)	3.1 (116)	45.6 (1695)
	female	64.2 (5031)	2.0 (154)	2.2 (172)	31.6 (2479)
non-white	male	61.2 (891)	1.4 (20)	1.6 (23)	35.8 (521)
	female	72.6 (3433)	1.4 (64)	1.7 (79)	24.4 (1155)

First entry in each cell is percent of total responses in row. Second entry is number of responses in cell.

Food stamps, social security and unemployment compensation were the sources with relatively large numbers of transitions reported. (I.e., with enough transitions to compare distributions for many cells.) The first two of these sources showed about the same patterns. Larger proportions of receipt of sources were reported by self-respondents than by proxies. There is usually a higher proportion of transitions between waves when at least one of two consecutive months has a proxy response than when both of the months are self-reported. As an example, see Table 4. Because the number of SS cases was much larger than the sum of SP, PS, and PP cases, these patterns did not have a noticeable effect on the within/between wave jumps. (For unemployment compensation there is a much larger number of cases with NN. The patterns are similar, but the difference in proportions are much smaller.)

TABLE 4.A

Food Stamps: Between Waves
Sex x Interview State

Sex	Interview State	RR	RN	NR	NN
Male	SS	54.5 (456)	9.4 (79)	6.0 (50)	30.1 (252)
	SP	45.7 (106)	12.5 (29)	8.6 (20)	33.2 (77)
	PS	38.2 (76)	16.1 (32)	8.0 (16)	37.7 (75)
	PP	37.7 (171)	12.4 (56)	5.7 (26)	44.2 (200)
Female	SS	65.5 (2326)	6.8 (240)	5.2 (184)	22.6 (802)
	SP	53.9 (125)	9.1 (21)	8.5 (20)	28.4 (66)
	PS	43.1 (103)	9.2 (22)	9.2 (22)	38.4 (92)
	PP	55.4 (92)	11.4 (19)	6.6 (11)	26.5 (44)

TABLE 4.B

Food Stamps: Within Waves
Sex x Interview State

Sex	Interview State	RR	RN	NR	NN
Male	SS	57.3 (1782)	1.5 (47)	2.5 (77)	38.7 (1202)
	PP	45.7 (939)	2.2 (46)	2.7 (56)	49.3 (1014)
Female	SS	68.1 (7750)	1.7 (198)	2.1 (236)	28.0 (3189)
	PP	59.8 (714)	1.7 (20)	1.3 (15)	37.3 (445)

MODELS

Since the empirical analysis failed to reveal any relationships between demographic variables and the distribution of gross changes, we must look for another way of determining their true distributions. For CPS it has long been known that there is a relationship between the responses to a question and (i) the amount of time that has elapsed between the month of interest and the month of interview, (ii) the interview status and (iii) the length of time a person has been in the sample. Here we propose models for gross changes that make use of similar relationships.

The dependent variable of interest for a given income type is the receipt state identified with the second of two consecutive months. The possible receipt states for month t are (1)=RR, (2)=RN, (3)=NR, (4)=NN. Let $y_{ijkt(\ell)}$ be the number of responses in receipt state ℓ in month t where

i = number of times a person has been interviewed,

j = number of months between month t and month of interview,

k = interview status for months t-1 and t; PP,PS,SP and SS with S=self, P=proxy.

Then the vector $\underline{y}_{ijkt}$ = $(y_{ijkt(1)}, y_{ijkt(2)}, y_{ijkt(3)}, y_{ijkt(4)})'$ represents the gross change counts for the combination ijkt.

Multivariate Normal Models

Since the $\underline{y}_{ijkt}$ are vectors of counts, they have a multinomial rather than a multivariate normal distribution. But because of the large sample sizes on which they are based (the total number of counts in y_{ijkt}), they have that distribution asymptotically. We propose a multivariate analysis of variance (MANOVA) model of the form

$$E(y_{ijkt(\ell)})=\mu_{(\ell)}+N_{i(\ell)}+M_{j(\ell)}+S_{k(\ell)}+ NM_{ij(\ell)}+NS_{ik(\ell)}+MS_{jk(\ell)}+\gamma_t \tag{1}$$

where the terms are

N_i = interview number i,

M_j = months of recall between month of interview and month of occurrence,

S_k = interview status,

NM_{ij}, NS_{ik}, MS_{jk} are interactions of these effects, and

γ_t = month t.

There are some difficulties we must take account of before using this model.

(1) Levels 2 and 3 of k occur only with j=4. This means that the cells which are defined with j=4 and k=1 or 4 contain structural zeros. The contrasts in the analysis that define the effects and their degrees of freedom must be consistent with these structural zeros.

(2) The effect for interview number is to determine if reporting of changes in state follows some pattern over time. For example, a person may report the specific month of transition in wave 1, but after that he reports all transitions as occuring in the first month of a wave. Suppose now that there is a proxy respondent for waves 2 and 3. Will the proxy behave as the self respondent did for wave 1, or as he would for wave 2, or in some different manner? In a strict sense this effect only has validity if the same respondent is available in each wave. However, we can still include this effect as an average response difference between successive interviews.

(3) Most of the data that is used in this modeling is not available on the file we are using. Recall that only persons who have received one of the eight income sources in the first 16 months of SIPPS are included in this file. The vast majority of persons have no receipt for the first 16 months and would thus have the receipt state NN for each of the months used in modeling. From the files for individual waves we would have to calculate the number of these persons in each cell defined by an ijkt combination. The most time-consuming part of this job would be matching records across waves.

Polytomous Logit Models

There is another approach we can take to this problem that does not require a multivariate normal distribution. Instead of modeling the frequency of each receipt state we can model the probabilities of the states with polytomous logit models. A brief description of these models is given.

Let an observation consist of a set of

independent variables $\underline{x}_i$ and a dependent variable y_i, where y_i falls into one of G mutually exclusive categories. Let $\underline{\beta}_g$ be a set of coefficients for category g,g=1,2,...G. Assume that

$$\text{Prob } (y_i=g) = \exp\,(\underline{x}_i' \, \underline{\beta}_g)/\sum_{g'=1}^{G} \exp\,(\underline{x}_i' \, \underline{\beta}_{g'}). \qquad (2)$$

The unknown $\underline{\beta}_g$, g=1,2,...G, can be estimated by maximum likelihood, where the likelihood function is

$$[\prod_{i=1}^{N} \exp\,(\underline{x}_i' \, \underline{\beta}_{h(i)})]/[\sum_{g=1}^{G} \exp\,(\underline{x}_i' \, \underline{\beta}_g)]^N$$

and h(i) is the category into which y_i falls. Note that the probability in (2) remains constant if all $\underline{\beta}_g$ are multiplied by a constant, so a single linear restriction must be placed on the $\underline{\beta}_g$'s to obtain unique maximum likelihood estimates.

We propose using this logit model approach to estimate the true proportion of responses in each receipt state at each time t. Let $\underline{x}_{ijkt}$ be the vector of 0-1 variables that indicate which main effects and interactions are present for each observation with a particular ijkt combination. Let $\underline{\beta}_\ell$ be the vector of corresponding effects for receipt state ℓ. Each observation that is counted in $y_{ijkt(\ell')}$ will contribute a term of the form

$$\exp\,(\underline{x}_{ijkt}' \, \underline{\beta}_{\ell'})/\sum_{\ell=1}^{4} \exp\,(\underline{x}_{ijkt}' \underline{\beta}_\ell) \qquad (3)$$

to the likelihood function. Thus we only need to compute all the $\underline{y}_{ijkt}$ in order to determine the likelihood function and the resulting maximum likelihood estimates $\hat{\underline{\beta}}_\ell$, ℓ=1,2,3 or 4. Then the estimated proportion of observations in receipt state ℓ for combination ijkt is obtained by substituting the $\hat{\underline{\beta}}_\ell$ into (3).

The same difficulties that were described for MANOVA models are also present here.

When using either of these modeling approaches we would test for main effects and interactions being zero in order to determine which of them influence the reporting of changes in receipt. For MANOVA models standard procedures are available and for logit models likelihood ratio tests are used for nested models; i.e., for testing that certain entries in $\underline{\beta}_\ell$, ℓ=1,2,3,4, are zero.

SUMMARY

An empirical examination did not detect any relationships between gross change distributions and nine demographic variables and interview status. Modeling approaches are proposed for estimating the true number and proportion of each receipt state for a particular combination of interview number, months recall, interview status and month. Tests of significance for main effects and interactions can be carried out to determine which of them influence reporting of changes in receipt status. The resulting models could be used to adjust the reported gross changes toward the actual gross changes. More consideration of the validity of the models and the amount of work required to carry out estimation needs to be done before carrying this work further.

Mention should be made of another study that is in progress at the Census Bureau. A comparison of administrative records obtained from four states with SIPP data is being made to investigate the relationship between reported and actual changes in status. We hope to be able to use these results in conjunction with models to get an improved estimate of gross change distributions.

REFERENCES

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TABLE 1

Month-to-Month Gross Changes: Food Stamps

Receipt Status	1st to 2nd	2nd to 3rd	3rd to 4th	4th to 5th	5th to 6th	6th to 7th	7th to 8th	8th to 9th	9th to 10th	10th to 11th	11th to 12th	12th to 13th	13th to 14th	14th to 15th	15th to 16th
RR	1240	1255	1274	1159	1270	1278	1287	1161	1260	1261	1265	1135	1216	1205	1219
RN	40	47	35	174	26	38	42	167	33	36	29	157	25	44	40
NR	62	54	61	129	46	51	51	123	37	33	40	97	33	54	43
NN	653	639	625	517	652	627	614	519	659	659	655	572	713	684	685