HOW DO WE DEDUCT SOMETHING WE DO NOT COLLECT? THE CASE OF OUT-OF-POCKET MEDICAL EXPENDITURES

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August 5, 1997

ABSTRACT

The Survey of Income and Program Participation (SIPP) is the premiere data source for computing poverty using the proposed alternative measurement methods. However, it does not capture household expenditures and liabilities for needed medical care or any associated reimbursements. The alternative approaches for measuring poverty acknowledge that income or benefits used to offset the cost of needed medical care should not be counted as resources available to cover other basic necessities (food, shelter, clothing). Yet, the difficulty in capturing these costs and reimbursements (so to deduct them from income) is so great, the measures cannot be integrated into the SIPP instrument within reasonable levels of cost and respondent burden. Thus, such expenses must be imputed, unlike the other components of the alternative poverty measure. Good imputation procedures for out-of-pocket medical expenses are not necessarily easy to produce because medical expenditures are highly correlated with characteristics not well measured in SIPP or other surveys focused on income. The questions addressed in this paper are: "How we can best capture deductible expenses for medical care and insurance within SIPP?" and "Does that procedure bias the resulting measures of poverty?" While ultimately one might envision imputing missing data from administrative sources, at this time the only sources available are the medical expenditure surveys conducted by the Department of Health and Human Services. In this paper, the National Medical Expenditure Survey forms the basis for the development of the imputation models examined and for the analysis of the impact of the imputation procedures on poverty rates.

HIGHLIGHTS

Poverty rates are not affected dramatically by the disregard of out-of-pocket expenditures toward premiums and direct medical care (MOOP) from resources and thresholds (exclusive of other proposed changes in the poverty measure). The impact mirrors the trend in MOOP in the general population.

- The poverty rate rises 0.8 percentage points (from 14.3 to 15.1 percent) if the resource and threshold measures excluded MOOP. The rise is most dramatic among the elderly and among persons in poor health who tend to have higher out-of-pocket expenditures.
- The percent of persons below 200 percent of poverty nearly doubles (increasing from 19.4 to 34.5 percent) if resource and threshold measures exclude MOOP. The rise is most dramatic for children, black nonhispanics, persons in poor health, persons in female-headed families, and persons without insurance coverage the full year.
- The poverty gap increases $3.3 billion if the resource and threshold measures excluded MOOP, a relative rise of 7.1 percent.

I conclude that the Census Bureau can confidently rely on imputed data to compute alternative poverty measures involving MOOP as long as the models take into account all the important predictors of expenditures and capture the highly skewed distribution of MOOP among the population. Such imputation strategies are feasible with the 1996 Panel of the Survey of Income and Program Participation since it has been expanded to capture health care utilization, and health status once per year. Even models that rely on the more limited information available in surveys like the March Current Population Survey can yield good measures of the impact of MOOP on poverty rates, but they can yield biased estimates of the poverty gap.

- The rise in poverty rates would appear to be .7, 1.0 or 1.7 percentage points if imputed rather than reported MOOP were used with the range of estimates varying by method of imputation.
- The distributional characteristics of the poor population and the size and composition of the low income population are not adversely affected by the use of imputed versus reported MOOP.

- Estimates of the change in the poverty gap caused by the treatment of MOOP can be adversely affected by use of imputed MOOP rather than reported MOOP. The impact of MOOP on the gap would seem to be $6.7 billion, $1.0 billion, or $4.0 billion depending on the type of model used.

- About four percent of the total population is misclassified when alternative poverty measure is based on imputed rather than reported MOOP, roughly half of whom were classified as poor when they were not.

INTRODUCTION

The National Academy of Sciences (NAS) Panel on Poverty and Family Assistance: Concepts, Information Needs, and Measurement Methods recommended the following change to poverty measurement in regard to medical expenses (Citro and Michael, 1995): (1) subtract out-of-pocket costs toward medical care (MOOP) from income in computing economic poverty while adjusting the threshold accordingly, and (2) add a Medical Care Risk Index (MCRI) to the list of Federal statistics on well-being. Theoretically, the NAS panel preferred the MOOP disregard from income to be restricted to only those unreimbursed expenditures toward services and supplies needed to maintain health. However, to be practical, NAS recommended (with one dissenting vote) deducting all out-of-pocket medical costs, inclusive of the households' share of premium contributions.

The NAS recommendations in their entirety reflect extensive changes to both the resource and threshold estimates needed to compute poverty rates and the poverty gap. With the exception of the two recommendations involving medical expenditures, the needed data to compute the new poverty statistics are reflected in the Survey of Income and Program Participation (SIPP). In fact, Citro and Michael recommended using SIPP as the basis of the official poverty measure.

However, SIPP does not directly measure the data needed to compute both the deductible out-of-pocket costs or the adequacy of insurance plans held. Furthermore, given the survey's focus on income and program participation, the cost of expanding the survey to collect good measures of out-of-pocket medical costs is excessive. Thus, I propose that the Census Bureau enhance SIPP by imputing the needed information from the series of Medical Expenditure Panel Surveys (MEPS).(2)

In this paper I explore alternative imputation strategies, their direct results in terms of estimating out-of-pocket costs for medical care and insurance, their indirect effects in terms of the bias (if any) on the poverty statistics introduced by using imputed rather than directly reported data. I also describe enhancements recently made to SIPP to ensure the best quality imputation model can be used within reasonable resource constraints. The findings are presented following a background section on the scope of the study. The paper concludes with a description of recent enhancements to the SIPP instrument and recommendations for additional research. Note, I am limiting my examination of the effects on poverty to MOOP alone; other changes proposed by the NAS panel are not in the scope of this study.(3)

SCOPE OF THE STUDY

The main focus of the study is to answer the following question: Given current constraints on available information and resources, is it reasonable to expect the Census Bureau to produce good estimates of the impact of MOOP on poverty rates using imputed as opposed to directly-measured values of MOOP?

To answer this question, I evaluated three different classes of imputation models ranging in complexity and predictive power and examined ranges of imputed estimates through replications of each type of model. To estimate the impact of the models, I imputed MOOP to an analysis file on which MOOP was known and compared the results to the reported MOOP. More importantly, however, I constructed alternative poverty measures from each of the measures of MOOP and examined the stability of those estimates across imputation models. The underlying data originate from the 1987 National Medical Expenditure Survey (NMES).

Imputation Models Evaluated

Clearly, the answer to the main question depends on the quality of the procedure used to impute MOOP and in its ability to capture the correlation between income, other resources, and MOOP. A good model should rely on good predictors of MOOP and preserve the highly skewed distribution of expenditures as well as the mean.(4)

During the health care reform debates of the early 1990's, health services researchers fine-tuned their methods for predicting medical expenditures so that they could simulate the impact of changing an insurance policy on expenditure patterns and out-of-pocket costs.Doyle and Farley (1995) indicate that the strongest predictors of medical expenses are utilization of health services (particularly overnight hospital stays), self-reported health status, and insurance coverage.

Unfortunately, most of these important predictors have not traditionally been available on surveys which provide a good income measure for the U.S. population, specifically the Survey of Income and Program Participation (SIPP) and the March Current Population Survey (CPS). Since imputation models are constrained to rely on information common to the survey receiving the imputed data and the host survey supplying the imputed data, these important predictors cannot always be used in the imputation model. As a result, of course, the predictive power of the model suffers.

To answer the question posed for the study, I tested three types of imputation models, a simple assignment of the mean (Weinberg and Lamas, 1993), an imputation model designed by David Betson to operate within the limited information of the CPS and to capture the skewed distribution of MOOP (Betson, 1995)(5), and a statistical match designed to optimize the use of the important predictors noted above. The models are described in the Appendix. At the same time I lobbied for and achieved an enhancement to the SIPP questionnaire to capture these predictors on a recurring basis (once per year) and to collect them using measures adapted from the most recent MEPS (Nelson and Short, 1997). Thus, at least one good income survey now also reflects key determinants of MOOP.

Sensitivity Analysis

The ultimate test of each model's performance is the impact of imputed versus directly observed MOOP on aggregate measures of alternate poverty and the relative change in poverty rates from the official definition. For this I examine poverty rates in total across six poverty measures: the official measure, an alternative based on directly observed MOOP and four alternatives based on three different imputation strategies. I further examine variations in the six poverty rates by demographic group and the distribution of poor persons by demographic group. Finally, I examine the impact of imputed MOOP on the size and composition of the low-income population (below 200 percent of poverty), on who is classified as poor, and on the poverty gap. The classification and poverty gap are highly sensitive toward the distribution of MOOP across the population.

To produce the six different poverty measures, I started with an analytic file with the known expenditure patterns and cash income as defined for the official poverty measure and then imputed a new expenditure pattern using each of the three types of models. I implemented the Betson model two times, Option 1 being a reestimation with more detailed distributional information and Option 2 (provided by Betson) reflecting this additional distributional detail as well as expanded set of independent variables and a revised functional form (see the appendix for a description). With this, I could observe at the micro-level how well the models replicate observed expenses. I could further observe the impact these imputation procedures have on an alternative poverty measure that subtracts MOOP costs from cash income. As noted, my focus is on the aggregate measures of the number and characteristics of the poverty population and the poverty gap. However, I give some attention to the size of the low income population and the rate at which each person's classification changes from poor to not poor (and the reverse) as a result of the imputation strategy.

In addition to the indirect impacts of MOOP costs on poverty outcomes, I examine the variability of the imputed estimates of MOOP, the degree of calibration of these estimates needed to bring them in line with the aggregate control totals, and the sensitivity of imputed MOOP to some aspects of the model design.

Data

The income and MOOP data originate from the 1987 National Medical Expenditure Survey (NMES), adjusted to capture observed trends in total expenditures, income, and demographic characteristics between 1987 and 1991. For a full discussion of the creation and attributes of the underlying data, refer to Doyle, Beauregard, and Lamas (1993). The data for this study are old but, nonetheless, the most recently available of this kind. Furthermore, Doyle, Beauregard, and Lamas illustrate that the data used for this study are comparable to the March CPS in measures of income and poverty in 1991. All income and expenditure data reported herein are in 1991 dollars.

There are three important caveats to note. First, the analysis is defined based on out-of-pocket costs toward direct medical care plus the household's share of premiums as captured by NMES. NMES does not capture Medicare Part b premium payments by the elderly population because the survey is designed to capture net rather than gross Social Security payments.[6]

Second, the underlying data do not capture any trends in MOOP that may have occurred since 1991. Changes could have occurred as a result of an overall increase in medical expenditures, an increase in managed care among the insurance plans held, or a reduction in the rate of employer and government subsidy of health insurance costs.[7]

Third, in the text, I refer to the data derived directly from NMES public use files as reported. However, this is a misnomer. In one-fourth to one-half of the medical events in this study the so-called reported amount was originally not reported and thus had to be imputed. For further discussion of the NMES imputation strategies see AHCPR (1991).

FINDINGS

There is a modest impact of MOOP on poverty, affecting primarily groups of people with high MOOP. There is large impact of MOOP on the size and composition of the low-income population, however. The relatively small impact of MOOP on poverty is not consistent with the findings of previous researchers (Weinberg and Lamas, 1993, Citro and Michael, 1995, and Betson, 1995). This smaller impact in the current study is due in part to the improved correlation between income, other resources, and MOOP than has been achieved in the data underlying the earlier studies. Another difference between these results and the results in the Citro and Michael (1995)and Betson (1995) studies is in the threshold definition. For this study, I adjusted the threshold for the alternative poverty measurement by subtracting the MOOP component.[8]

The estimates of the impact of MOOP on the poverty rate varies by the source of MOOP. The variation depends on the degree to which the model captures the skewed distribution of MOOP. On the other hand, estimates of the characteristics of the poor and the size and characteristics of the low income population remain fairly stable across the imputation models. Like the poverty rate, estimates of the poverty gap vary by model. Two of the models come very close to replicating the total poverty gap under the revised poverty definition. Unfortunately, neither of these performs well estimating the size of the gap for key demographic groups.

Replications of the imputation models show some variation in the outcomes which need to be taken into account in future applications of the imputation strategy.[9]

Poverty and Low Income Populations Change in Size and Composition with the Alternative Treatment of MOOP in Defining Poverty

Based on original expenses, overall poverty rate increases 0.8 percent to 15.1 as a result of this definitional change, a modest but significant increase in the poverty rate.[10] The impact, summarized in Tables 1 and 2, is concentrated among the elderly and persons in poor health who tend to have higher MOOP costs. Consequently the composition of the poverty population shifts away from persons in single-parent families with children and toward elderly persons and persons in poor health. (Again refer to Doyle, Beauregard and Lamas, 1993, for an in-depth discussion.) For example, as illustrated in table 2, under the proposed alternative measure, proportionately more poor persons are elderly and proportionately fewer poor persons are children than under the official measure.[11]

This phenomena arises at least in part because of the significance of Medicaid in covering the MOOP costs of low income families with children.[12] Of course, with the changing health care market, the pattern of out-of-pocket costs may have changed since this survey was originally conducted. The new MEPS currently being fielded will support further analysis of this trend.[13]

It is interesting to note that the low-income population, i.e., persons in families with income net of MOOP costs below 200 percent of the poverty threshold (adjusted as noted above), is very large relative to a more traditionally defined low-income population. Table 3 shows the rate of low income persons nearly doubling, rising from 19.4 percent to 34.5 percent overall. The increase in low-income rates (i.e., percent of population in households below 200 percent of the threshold) is disproportionate across some key demographic groups with the rate nearly doubling among children (from 22.1 to 44.1 percent), among black nonhispanics (from 24.1 to 57.1), among persons in female-headed families (from 29.2 to 62.7), among persons with no insurance coverage (from 32.0 to 62.2 percent) and persons in poor health (from 32.6 to 64.1). Nearly two-thirds of persons in female-headed families would be considered low income under this alternative formula as would over half of the very old (age 75 and older), Hispanic and black nonhispanic persons, persons with less than full-year insurance coverage, persons with less than full-time full-year employment, persons prevented from work, and persons in poor health. Correspondingly, the composition of the low-income population shifts somewhat (Table 4) away from adults, away from white nonhispanic persons, away from persons in married-couple families, away from full-time full-year workers, and away from persons insured full year. Again this outcome seems to reflect the lack of adequate insurance coverage among key groups not poor enough to qualify for Medicaid and who do not have access to adequate health insurance (due to cost, opportunity, or preference).

A large impact of the change in poverty definition appears in the poverty gap which rises 7.1 percent (from $46.5 billion to $49.8 billion) as a result of the alternate measurement procedure (Table 5). This increase in the gap is concentrated among families headed by older adults (age 45 and older) with families headed by older elderly experiencing a more than two-fold increase. Among those for whom Medicaid is a major insurer (poor families with children and female-headed families) the gap actually declines with the alternate definition. The large increase in the gap among families headed by persons insured full-year (16 percent from $24.3 billion to $28.3 billion) is likely just a reflection of the increase in the gap among the elderly who are predominantly covered under Medicare. The large relative increase in the gap among families headed by persons prevented from work (38 percent from $8.4 billion to $11.6 billion) is also likely to reflect the increase among Medicare participants (although this needs confirmation).

Estimates of Poverty Rates Vary by Imputation Model

The imputation of the mean MOOP (which has the least amount of control of any of the models on the variation in expenditures) yields the largest bias in the overall alternate poverty rate (0.9 percentage points--16.0 versus the target of 15.1 percent poor), while the three models that capture the variation in expenditures have a bias of 0.2 percentage points or less. The Betson model, Option 1, slightly underestimates the poverty rate (15.0 versus 15.1 percent), the Betson model, option 2, replicates the target poverty rate of 15.1 percent, and the Match overestimates the poverty rate (15.3 versus 15.1 percent).

For many demographic groups, the alternate poverty rate does not vary a lot by imputation model. The mean imputation model tends to yield the most biased estimates among each demographic group like it does among the total population. The Betson model (both options) tends to yield the lowest alternate poverty rates among the demographic groups as it does overall.

There are some exceptions to this general finding. Among the older elderly (age 75+), alternate poverty rates are not stable. They vary from 21.1 percent under the Betson model, Option 1, to 26.6 percent under the mean imputation model. Similarly, among persons with missing information on disability days (a population of about 1.7 million people) the alternative poverty rates based on imputed data range from 13.2 to 18.8, all of which are higher than the alternative poverty rates based on reported MOOP (11.7 percent). Finally among persons with self-perceived health status of poor, the alternate poverty rate varies from 31.2 to 36.1 percent, all of which are lower than the poverty rate derived from reported MOOP (37.3 percent). Thus, all models appear to be imputing too little MOOP expenses among this group.

Characteristics of the Poverty Population are Fairly Stable Across Imputation Models

The distribution of poor persons by demographic group under the alternative imputation model is not dramatically affected by the imputation model employed. Some minor exceptions lie in select groups defined by insurance coverage and by employment status of the head. Oddly enough given its increased focus on insurance status, the Betson model, Option 2, shifts some of the insured poor between the part year and full year categories. Similarly, each of the imputation models shifts the poor somewhat away from unemployed toward full-time-full-year workers

Size and Characteristics of the Low-Income Population are Fairly Stable Across Imputation Models

The percent of the population below twice the poverty threshold, i.e., the low-income rate, increases substantially as we move from the official definition of poverty to the alternative definition (19.4 under official and 34.5 among alternate from Table 3). However, the alternative low-income rate does not fluctuate widely across imputation models (35.1 percent, 35.3 percent, 34.3 percent, and 34.8 percent). With few exceptions, the trend of little or no impact of imputed versus reported MOOP applies across demographic groups. Exceptional groups tend to be small in size (such as persons of other race/ethnic origin) suggesting the apparent differences may not be statistically significant. Of note, among persons in poor health (a population of about 7 million persons), the simplest imputation model yields the closest approximation to the rate of low income. Given all the other evidence that this particular model performs least well of all examined, its not clear why this would occur. The distribution of low-income persons by age (Table 4) shows virtually no difference among the imputation models in the distributional characteristics of the low-income population.

The Magnitude of the Poverty Gap is Affected by the Imputation Model

Under the official poverty measurement algorithm, we have a poverty gap of $46.5 billion. This increases to $49.8 billion under the alternate poverty definition based on reported MOOP, a rise of $3.3 billion or 7.1 percent. The Betson model, Option 2, and the match imputation model yield a poverty gap ($50.5 billion) very close to the reported MOOP but the other methods of imputation produce biased results. The mean imputation procedure yields a poverty gap of $53.2 billion, more than 14 percent higher than the reported gap. The Betson imputation model, Option 1, underestimates the gap by nearly 5 percent. In fact, the results of the Betson model, Option 1, when compared to the official poverty gap, show very little impact of MOOP on the poverty gap, an unrealistic finding.

With the mean imputation and the Betson model, Option 1, the general pattern noted above (over estimate with Mean and underestimate with Betson, Option 1) repeats across most demographic groups. There are some exceptions, however. The Mean imputation underestimates the gap for families with missing health status of the head and performs well for families whose heads are: aged 45 to 64, of other race/ethnicity, uninsured, totally limited in work, or not in good health (either because they had 11+ disability days or reported being in poor health). Betson model, Option 1, yields good estimates of the gap among female-headed families and among families headed by adults who are under age 45, insured part year, working less than full time or full year, have no disability days, or who do not report health status.

Unfortunately, the two models that closely replicate the impact of deducting MOOP on the poverty gap (Betson model, Option 2, and the match) do not perform well replicating the poverty gap among all important subgroups of the population. In some instances, the alternate poverty gap would be overestimated or underestimated by as much as 16 percent. This does occur among some small groups leaving open the question of statistical significance (for example, families headed by individuals in the other race category and families headed by other male heads).

However, the bias also occurs among some relatively large groups like the following: families headed by full-time full-year workers (alternate poverty gap overestimated by 12 percent in the Betson model, Option 2, and by 13 percent in the Match) and persons in female-headed families (alternate poverty gap overestimated by 14 percent with Betson Option 2). Of note is that the Betson Option 2 method did not capture the gap very accurately among families classified by extent of insurance coverage, even though this model incorporated an explicit control on type of insurance coverage. The other groups for which both models yielded biased results are: families headed by persons unable to work due to limitations, families headed by persons with selected categories of self-reported health status (excellent, good, fair, and nonresponse), and families headed by persons in selected categories of disability days.

The Quality of the Imputed MOOP Is Generally Quite Good

Overall the quality of the imputation models, especially the Betson and Match methods, is quite high. Tables 6 and 7 present some key statistics on which this quality assessment is based. The first column of Table 6 presents the targets derived from NMES data and the other four columns present the outcomes of each of the imputation models. All the models result in some misclassification of persons compared to the reported MOOP. The size of that group ranges from 3.5 to 4.8 percent of the total population. Note, while this is not large relative to the total population, it is large in magnitude relative to the size of the poverty population, affecting about one-quarter as many people as there are poor persons in total. However, in all the models the misclassification is fairly well-balanced between persons classified as poor who were not and the reverse.

In all cases the imputation model as estimated on the NMES data originally did not precisely replicate the total MOOP when reapplied to the NMES data and thus the outcomes had to be calibrated.(14) The calibration factors for each model studied were computed separately by age group. The least amount of adjustment needed was for the mean imputation and the most amount of calibration needed was for the statistical match. Further refinement of the statistical match itself could result in a reduction in the size of these calibration factors. In all, these calibration factors are not as small as I would like but they are not so large as to totally distort the distribution of the imputed data.

With the calibration factors, of course, all the imputation models achieved the target total and mean MOOP for the analysis file. However, none of them replicated the target median. The target median is less than half of the target mean, reflecting the highly skewed MOOP distribution on the original data set. The mean imputation method, as expected, picks up virtually none of the variation in expenses so the discrepancy between imputed and reported medians is not a surprise. The medians for all of the other models are closer to the target median but still not very close (the Betson model, Option 1, median is over 30 percent too low, the Betson model, Option 2, median is over 12 percent too low, and the Match median is nearly 12 percent too high).

Table 7 illustrates the range of (uncalibrated) estimates that could be achieved under a scheme of multiple imputation.[(15)] Note, that in all cases appropriate calibration factors would be applied in application of the model so the imputed values themselves would not vary to the degree they do in the table. Also note, I use different units of analysis across the columns of this table. The Betson model, Option 1, imputes MOOP at the family-level and thus is evaluated at the family level. The Match is a person-based imputation model and this is evaluated at the person level.

The range of estimates under the Betson model, Option 1, stems from varying the random number used for the two stochastic components of the system, the first determines the selection of who gets nonzero values of MOOP and the second affects how much they get. (This is described in more detail in the Appendix.) This model was replicated 100 times, each time with a different seed for each of the random draws.

The range of estimates under the Match stems from two sources. The match essentially imputes expenditures from one random half sample of the NMES data to the other and visa versa. The sample replicates were generated from repeating the same matching algorithm across 50 replicate draws of the half samples. The weight replicates of this method involved the same underlying half samples. However, the weights governing the distance function vary.[(16)] The weight replication of the match led to the choice of the actual matching algorithm used for the results analyzed in the FINDINGS section of in this study and used as the base procedure for the sample replicates. In essence, I chose the model with the least deviation in imputed total expenditures between reported and imputed amounts.

The span of the imputed totals across all the replications is quite small: $14.9 billion for Betson replicates, $15.0 billion for sample-match replicates, and $18.5 billion for weights-match replicates. All of these estimates are about one-tenth of the mean across the corresponding set of replicates.[(17)] The most revealing statistics in Table 7 are those for the calibration factors. These illustrate the range of adjustments needed for any given imputation. At worst, the Betson method, Option 1, would require an adjustment factor of 1.137 in order to replicate the target total MOOP. Of course, the sample-match replicates are quite good by design since I used the best weighting algorithm from the weight-replicates.) The weight-match, with a potential adjustment factor of 1.158 could be a bit worse than the Betson method, Option 1. However, on average, the adjustment (of about 1.069) would be slightly less than the Betson method adjustment (of 1.09).

NEEDED RESEARCH

Clearly, we are not yet ready to produce final estimates of the impact of MOOP on poverty because the best source of information on MOOP (i.e., NMES) is quite out of date and does not reflect any of the recent changes in the health care delivery system that affect cost of care and access to care, and in health insurance availability, benefits, and utilization controls. MEPS, which is currently in the field, will offer improved information to conduct this research and the data pertaining to 1996 will become available in the fall of 1998.

The lack of current information on MOOP needs some attention. The continuous fielding of MEPS will improve the relevance of the expenditure surveys because there will no longer be a 10-year gap in the data collection cycle. However, because of the use of follow-back surveys to improve the quality of the expenditure data, we will always face some lag between the year to which the expenditure data pertain and the year for which poverty is to be computed. As a result, we need to develop methodology to project the MOOP spending to future time periods. Some efforts have been made in the context of projecting total expenditures by source of payment (AHCPR, 1996b) but the projection was not provided in the context of income and unit composition changes over the same time period.

The March CPS questionnaire has been expanded in recent years to incorporate self-perceived health status in the list of items collected. We need to expand the CPS-based imputation model to take this into account since it is an important predictor of expenditures.

Finally, further analysis of the matching technique as a method of imputing MOOP is needed. The next steps are to apply it to SIPP and CPS and evaluate the outcome in terms of the quality and variability of MOOP and the impact on poverty rates.

ACKNOWLEDGMENTS

My appreciation goes to all the folks who offered comments on the early drafts of this paper. These are Dan Weinberg, Bob Bennefield, and Sue Dorinski of the Census Bureau and David Betson, Department of Economics, University of Notre Dame. David also shared with me the results of his ongoing work to refine and improve the imputation of medical out-of-pocket expenses. I am grateful to Kathy Short who reestimated the Betson imputation model, Option 1, and very thankful for the efforts of Stephen Heacock in the development of the software for the statistical match and for the replication of the imputation models. Finally, I am quite pleased with the help of Reita Glenn-Hackett in generating the printed tables. Kathy, Stephen, and Rita are all from the Census Bureau.

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Table 1: Poverty rates of Persons by Source of Out-of-Pocket (MOOP) Medical Expenditures for the Nation and by Demographic Group

	Official Measure	Less Reported MOOP	Less Mean MOOP	Less Betson MOOP Option 1	Less Betson MOOP Option 2	Less Matched MOOP
Total	14.3	15.1	16.0	15.0	15.1	15.3
By Age						
Less than 18	22.2	21.2	22.6	21.4	21.7	21.8
Adults age 18 to 44	12.4	12.7	13.2	12.9	12.9	13.0
Adults age 45 to 64	8.7	9.7	10.1	9.2	9.6	9.8
Adults age 65 to 74	10.5	15.2	16.9	14.8	14.2	14.4
Adults age 75+	16.8	24.9	26.6	21.1	21.3	23.8
By Sex						
Male	12.1	12.8	13.6	12.7	12.9	13.2
Female	16.4	17.3	18.3	17.0	17.2	17.3
By Race/Ethnicity						
Hispanic	28.9	31.4	32.2	29.7	30.0	31.9
Black Nonhispanic	33.4	32.7	35.5	32.5	33.7	33.1
White Nonhispanic	9.4	10.1	10.8	10.2	10.2	10.4
Other	18.0	21.1	18.9	19.4	18.4	17.9
By Family Marital Status						
Single	21.0	23.2	23.7	22.5	21.6	23.0
Married Couple	7.7	8.6	9.4	8.5	8.8	8.9
Female Head	35.8	34.2	36.1	34.5	35.3	34.9
Male Head	11.9	14.3	14.2	12.6	13.1	13.9
By Insurance Status						
Insured all year	10.4	11.3	12.1	11.2	11.6	11.5

Insured part year	27.8	28.2	29.3	27.1	26.2	29.0
Uninsured	31.6	32.1	33.8	32.4	31.9	32.2
By Employment Status of the Family						
Full time all year	6.7	6.7	7.7	7.1	7.4	7.2
Other Worker	23.9	24.5	25.2	24.1	24.3	24.4
Unemployed	27.9	30.8	31.4	29.1	29.2	30.4
By Work Limitations (Adults)						
None	9.6	10.3	11.0	10.5	10.5	10.6
Limited in Kind or Amount of Work	13.8	16.5	17.8	16.1	16.4	16.4
Prevented from Work	25.4	32.0	31.7	28.0	28.3	30.5
By Disability Days						
None	13.7	14.3	15.3	14.4	14.5	14.4
1 to 3	13.3	13.8	14.8	13.2	13.5	14.5
4 to 10	15.6	16.6	16.9	16.4	16.2	17.0
11+	23.3	26.5	26.2	24.3	24.6	25.3
Nonresponse	11.4	11.7	17.0	13.2	14.8	18.8
By Self-Reported Health Status						
Excellent	10.4	10.3	11.2	10.9	10.8	10.5
Good	12.3	13.0	14.0	12.9	13.2	13.4
Fair	20.6	23.4	24.5	22.2	22.7	23.4
Poor	29.6	37.3	36.1	31.2	31.3	34.5
Nonresponse	21.9	21.4	22.1	21.9	21.3	22.1

Source: National Medical Expenditure Survey aged to 1991/1992 as described in Doyle, Beauregard and Lamas (1993). Sample size of 21056 persons weighted to represent a total population in 1992 of 250,593,000. Of these 103 people were deleted from the analysis due to an inability to define family relationships.

Table 2: Number of Poor Persons by Source of Out-of-Pocket (MOOP) Medical Expenditures and Distribution by Demographic Group

	Official Measure	Less Reported MOOP	Less Mean MOOP	Less Betson MOOP Option 1	Less Betson MOOP Option 2	Less Matched MOOP
Total Number (1,000,000)	35.8	37.7	40.0	37.3	37.7	38.3
Percent Distribution						
By Age						
Less than 18	40.9	37.1	37.4	37.8	38.0	37.6
Adults age 18 to 44	36.5	35.4	34.9	36.4	36.2	35.9

Adults age 45 to 64	11.7	12.3	12.1	11.9	12.3	12.2
Adults age 65 to 74	5.5	7.5	7.8	7.4	7.0	7.0
Adults age 75+	5.5	7.8	7.8	6.6	6.6	7.3
By Sex						
Male	40.8	40.8	41.0	41.2	41.1	41.7
Female	59.2	59.2	59.1	58.9	58.9	58.4
By Race/Ethnicity						
Hispanic	17.7	18.3	17.7	17.4	17.4	18.3
Black Nonhispanic	28.7	26.6	27.3	26.7	27.4	26.6
White Nonhispanic	49.2	50.3	50.9	51.3	50.9	51.1
Other	4.4	4.9	4.1	4.5	4.3	4.1
By Family Marital Status						
Single	24.8	26.0	25.1	25.5	24.2	25.4
Married Couple	35.1	37.2	38.3	37.2	38.0	37.8
Female Head	37.8	34.2	34.2	35.0	35.4	34.4
Male Head	2.3	2.7	2.5	2.4	2.4	2.5
By Insurance Status						
Insured all year	58.2	59.8	60.2	59.9	61.2	59.8
Insured part year	18.6	17.9	17.5	17.3	16.6	18.1
Uninsured	23.2	22.4	22.3	22.8	22.2	22.1
By Employment Status of the Family						
Full time all year	28.4	27.1	29.6	29.3	29.9	28.9
Other Worker	23.7	23.1	22.4	22.9	22.9	22.7
Unemployed	47.4	49.7	47.9	47.4	47.0	48.3
By Work Limitations (Adults)						
None	40.2	40.8	41.3	41.9	41.7	41.3
Limited in Kind or Amount of Work	6.3	7.1	7.2	7.0	7.0	6.9
Prevented from Work	12.7	15.1	14.1	13.4	13.3	14.2
By Disability Days						
None	66.1	65.6	66.2	66.6	66.7	65.3
1 to 3	13.8	13.5	13.7	13.1	13.2	14.0
4 to 10	10.2	10.3	9.9	10.4	10.1	10.4
11+	9.4	10.1	9.4	9.4	9.4	9.5

Nonresponse	0.5	0.5	0.7	0.6	0.7	0.8
By Self-Reported Health Status						
Excellent	22.1	20.8	21.2	22.1	21.8	20.8
Good	37.1	37.0	37.8	37.0	37.7	37.6
Fair	18.8	20.2	19.9	19.3	19.6	19.9
Poor	5.8	6.9	6.3	5.8	5.8	6.3
Nonresponse	16.4	15.2	14.8	15.7	15.1	15.4

Source: National Medical Expenditure Survey aged to 1991/1992 as described in Doyle, Beauregard and Lamas (1993). Sample size of 21056 persons weighted to represent a total population in 1992 of 250,593,000. Of these 103 people were deleted from the analysis due to an inability to define family relationships.

Table 3: Rates of Low Income Persons by Source of Out-of-Pocket (MOOP) Medical Expenditures for the Nation and by Demographic Group

	Official Measure	Less Reported MOOP	Less Mean MOOP	Less Betson MOOP Option 1	Less Betson MOOP Option 2	Less Matched MOOP
Total	19.4	34.5	35.1	35.3	34.3	34.8
By Age						
Less than 18	22.1	44.1	44.7	45.2	43.8	44.8
Adults age 18 to 44	18.0	30.6	31.0	31.6	30.7	30.9
Adults age 45 to 64	13.1	23.4	23.1	23.9	23.0	23.3
Adults age 65 to 74	24.7	39.5	40.9	39.0	38.4	39.8
Adults age 75+	34.5	53.5	57.3	54.2	53.7	53.4
By Sex						
Male	18.8	31.6	32.2	32.5	31.7	32.1
Female	20.0	37.2	37.8	38.0	36.8	37.4
By Race/Ethnicity						
Hispanic	31.3	59.7	60.1	60.9	58.9	59.6
Black Nonhispanic	24.1	57.1	57.9	57.0	56.7	56.8
White Nonhispanic	17.1	27.5	28.1	28.4	27.5	28.1
Other	25.3	43.3	42.2	44.0	40.9	41.0
By Family Marital Status						
Single	23.6	44.4	45.1	45.5	44.1	43.8
Married Couple	16.1	25.5	25.8	26.0	25.1	25.8
Female Head	29.2	62.7	64.3	64.9	63.7	63.5
Male Head	18.4	31.4	33.2	31.5	30.8	35.9

By Insurance Status						
Insured all year	16.6	28.4	29.1	29.0	28.3	28.7
Insured part year	28.9	55.4	55.2	58.1	54.6	55.8
Uninsured	32.0	62.2	62.4	62.9	61.6	62.2
By Employment Status of the Family						
Full time all year	13.2	20.6	21.3	21.8	21.1	21.4
Other Worker	28.3	53.3	53.0	53.4	52.0	52.9
Unemployed	29.9	58.5	59.4	58.7	57.3	58.1
By Work Limitations (Adults)						
None	16.5	27.2	27.5	28.1	27.1	27.4
Limited in Kind or Amount of Work	22.6	38.5	39.7	38.3	37.9	38.3
Prevented from Work	31.2	57.5	59.0	57.4	56.4	57.5
By Disability Days						
None	19.7	34.0	34.6	35.0	34.0	34.3
1 to 3	17.1	31.5	32.1	31.8	30.9	31.9
4 to 10	16.4	33.9	33.4	34.0	33.3	34.3
11+	26.6	49.9	51.7	50.3	49.2	50.2
Nonresponse	23.3	32.1	34.9	36.3	35.5	33.2
By Self-Reported Health Status						
Excellent	15.2	26.6	26.5	27.2	26.3	26.8
Good	18.7	31.8	32.6	32.9	32.0	32.3
Fair	25.9	47.9	49.3	48.7	47.5	48.7
Poor	32.6	64.1	64.5	61.4	61.2	61.1
Nonresponse	23.2	43.8	44.4	45.2	43.5	44.0

Source: National Medical Expenditure Survey aged to 1991/1992 as described in Doyle, Beauregard and Lamas (1993). Sample size of 21056 persons weighted to represent a total population in 1992 of 250,593,000. Of these 103 people were deleted from the analysis due to an inability to define family relationships.

Table 4: Number of Low-Income Persons by Source of Out-of-Pocket (MOOP) Medical Expenditures and Distribution by Demographic Group

	Official Measure	Less Reported MOOP	Less Mean MOOP	Less Betson MOOP Option 1	Less Betson MOOP Option 2	Less Matched MOOP
Total Number (1,000,000)	48.5	86.1	87.5	88.2	85.7	86.9
Percent Distribution						
By Age						

Less than 18	30.0	33.8	33.7	33.8	33.7	34.0
Adults age 18 to 44	39.2	37.4	37.3	37.8	37.7	37.5
Adults age 45 to 64	12.9	13.0	12.6	13.0	12.9	12.8
Adults age 65 to 74	9.5	8.5	8.7	8.2	8.3	8.5
Adults age 75+	8.4	7.3	7.7	7.2	7.4	7.2
By Sex						
Male	46.8	44.3	44.3	44.4	44.6	44.5
Female	53.2	55.7	55.7	55.6	55.4	55.6
By Race/Ethnicity						
Hispanic	14.1	15.2	15.0	15.1	15.1	15.0
Black Nonhispanic	15.2	20.3	20.3	19.8	20.3	20.1
White Nonhispanic	66.1	60.1	60.4	60.7	60.4	60.8
Other	4.5	4.4	4.2	4.3	4.2	4.1
By Family Marital Status						
Single	20.6	21.8	21.8	21.8	21.8	21.3
Married Couple	54.0	48.1	47.8	47.9	47.7	48.2
Female Head	22.8	27.5	27.8	27.8	28.1	27.6
Male Head	2.7	2.6	2.7	2.5	2.5	2.9
By Insurance Status						
Insured all year	68.4	65.6	66.2	65.5	65.9	65.9
Insured part year	14.3	15.4	15.1	15.8	15.2	15.3
Uninsured	17.3	19.0	18.7	18.7	18.9	18.8
By Employment Status of the Family						
Full time all year	41.8	36.6	37.2	37.8	37.7	37.7
Other Worker	20.7	22.0	21.5	21.5	21.6	21.6
Unemployed	37.5	41.3	41.3	40.5	40.6	40.6
By Work Limitations (Adults)						
None	51.0	47.1	47.0	47.6	47.4	47.1
Limited in Kind or Amount of Work	7.5	7.2	7.3	7.0	7.2	7.1
Prevented from Work	11.5	11.9	12.0	11.6	11.7	11.8
By Disability Days						
None	70.3	68.3	68.4	68.7	68.6	68.2
1 to 3	13.1	13.5	13.6	13.4	13.4	13.6

4 to 10	7.9	9.2	8.9	9.1	9.1	9.3
11+	7.9	8.3	8.5	8.2	8.3	8.3
Nonresponse	0.8	0.6	0.7	0.7	0.7	0.6
By Self-Reported Health Status						
Excellent	23.8	23.4	23.0	23.4	23.3	23.4
Good	41.4	39.7	40.0	40.0	40.1	39.9
Fair	17.4	18.1	18.3	18.0	18.0	18.2
Poor	4.7	5.2	5.1	4.9	5.0	4.9
Nonresponse	12.8	13.6	13.6	13.7	13.6	13.5

Source: National Medical Expenditure Survey aged to 1991/1992 as described in Doyle, Beauregard and Lamas (1993). Sample size of 21056 persons weighted to represent a total population in 1992 of 250,593,000. Of these 103 people were deleted from the analysis due to an inability to define family relationships.

Table 5: Poverty Gap by Source of Out-of-Pocket (MOOP) Medical Expenditures For the Nation and by Demographic Group (in billions)

Characteristics of Family Head	Official Measure	Less Reported MOOP	Less Mean MOOP	Less Betson MOOP Option 1	Less Betson MOOP Option 2	Less Matched MOOP
Total Number	46.5	49.8	53.2	47.5	50.5	50.5
By Age						
Less than 18	1.4	0.5	0.5	0.9	0.5	0.6
Adults age 18 to 44	30.7	29.4	31.3	29.6	31.1	30.8
Adults age 45 to 64	9.1	10.1	10.4	8.9	9.8	9.8
Adults age 65 to 74	2.9	4.8	5.5	4.1	4.8	4.7
Adults age 75+	2.3	5.0	5.5	3.8	4.3	4.6
By Sex						
Male	18.4	20.3	21.3	19.3	20.5	21.1
Female	28.1	29.6	32.0	28.2	30.0	29.4
By Race/Ethnicity						
Hispanic	7.1	7.2	7.5	6.9	7.0	7.5
Black Nonhispanic	11.8	11.8	13.7	11.3	13.0	11.8
White Nonhispanic	25.6	28.7	30.0	27.4	28.6	29.4
Other	2.0	2.1	2.1	1.9	1.9	1.8
By Family Marital Status						
Single	21.3	22.6	23.4	21.7	21.4	23.1
Married Couple	9.9	12.8	13.8	11.5	12.9	12.8

Female Head	14.6	13.5	15.1	13.5	15.4	13.8
Male Head	0.7	0.9	1.0	0.8	0.8	0.8
By Insurance Status						
Insured all year	24.3	28.3	31.2	27.0	30.9	28.7
Insured part year	9.1	9.0	9.5	8.7	8.0	9.3
Uninsured	13.2	12.5	12.5	11.8	11.5	12.5
By Employment Status of the Family						
Full time all year	11.2	11.6	13.7	12.4	13.0	13.1
Other Worker	13.0	13.3	14.0	13.3	13.4	13.5
Unemployed	21.4	24.7	25.4	21.1	23.9	23.7
By Work Limitations (Adults)						
None	32.1	32.2	35.3	32.4	34.0	33.8
Limited in Kind or Amount of Work	4.5	5.5	5.8	5.1	6.0	5.4
Prevented from Work	8.4	11.6	11.6	9.0	10.0	10.7
By Disability Days						
None	29.5	30.8	33.5	30.7	32.3	31.8
1 to 3	6.2	6.2	6.7	6.1	6.7	6.2
4 to 10	4.7	5.0	5.2	4.7	5.0	5.5
11+	6.1	7.7	7.9	5.9	6.5	6.9
Nonresponse	0	0.1	0.1	0	0	0.1
By Self-Reported Health Status						
Excellent	7.7	7.3	8.4	8.1	7.8	8.0
Good	18.2	19.4	20.8	18.8	21.0	19.5
Fair	11.4	12.9	14.4	11.9	13.0	13.2
Poor	3.7	5.3	5.1	3.8	4.4	5.0
Nonresponse	5.5	4.9	4.6	4.9	4.1	4.8

Source: National Medical Expenditure Survey aged to 1991/1992 as described in Doyle, Beauregard and Lamas (1993). Sample size of 21056 persons weighted to represent a total population in 1992 of 250,593,000. Of these 103 people were deleted from the analysis due to an inability to define family relationships.

Table 6: Quality of Estimates of Poverty Rates and Out-of -Pocket Expenses by Source of Out-of-Pocket Expenses

	Less Reported MOOP	Less Mean Imputed MOOP	Less Betson MOOP Option 1	Less Betson MOOP Option 2	Less Matched MOOP
Poverty Rate	15.1	16.0	15.0	15.1	15.3

Percent of the Population that is Misclassified	na	3.7	4.4	4.8	3.5
Calibration Factors					
Elderly	1.0	0.935*	1.044	.904	1.114
Nonelderly	1.0	1.054*	1.083	.924	1.084
Total Calibrated MOOP** (billions)	178.2	178.3	178.3	178.3	178.2
Mean Family MOOP**	1621	1621	1621	1621	1621
Median Family MOOP**	738	1699	503	649	827

Table 7: Range of Estimates of Out-of -Pocket Expenses by Source of the Expenses

	Replicates of Betson Imputation (family-level)	Sample Replicates for Match Imputation (person-level)	Weight Replicates for Match Imputation (person-level)
Range of Uncalibrated Total (billions)	156.8 - 171.7	166.5 - 181.5	155.1 - 173.6
Mean of Uncalibrated Total (billions)	163.6	174.0	163.0
Median of Uncalibrated Total (billions)	163.6	174.0	161.6
Range of Uncalibrated Mean	1430 - 1566	648 - 749	620 - 692
Mean of Uncalibrated Mean MOOP	1492	697	653
Median of Uncalibrated Mean MOOP	1492	648	650
Range of Uncalibrated Median	457 - 506	125 - 145	122 - 143
Mean of Uncalibrated Median	479	135	132
Median of Uncalibrated Median	478	135	132
Range of Calibration Factors***	1.038 - 1.137	.917 - 1.090	.970 - 1.158
Mean of Calibration Factors***	1.090	1.001	1.069
Median of Calibration Factors***	1.089	1.000	1.060

Source: National Medical Expenditure Survey aged to 1991/1992 as described in Doyle, Beauregard, and Lamas (1993). Sample size of 21056 persons weighted to represent a total population in 1992 of 250,593,000. Of these 103 people were deleted from the analysis due to an inability to define family relationships.

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*The calibration factors for the "Less Mean Imputed MOOP" option were applied to MOOP costs on direct medical care and MOOP costs toward premiums, rather than to total MOOP costs of elderly and Nonelderly.

**These statistics were derived from family level expenditures using family level weights and were restricted to records with positive values for MOOP.

***Calibration factors were computed differently depending on the imputation model. In the case of the Betson model, they were derived from the data base from which the model was estimated (a March CPS look-alike file). Furthermore expenditures were imputed and calibrated at the family level. The actual target for the Betson imputation on that file was $182 billion rather than $178 billion used in Table 6. The statistical match was based on persons in the full-year NMES data set and the results were calibrated for that population. The target for the imputation on that longitudinal person file was $174 billion rather that $178 billion. These latter two estimates only differ in the weights used to compute them. The $174 billion estimate represents the sum of person-level expenses over persons using person weights. The $178 billion estimate represents the sum of family-level expenses over families using family weights.

APPENDIX

THE IMPUTATION MODELS

Imputed Means.

The simplest imputation model is the one which captures the mean but almost none of the variation in out-of-pocket costs. Such a method is quick, easy, and inexpensive to implement yet the quality of the imputation is severely restricted due to the lack of accounting for the underlying distribution of expenditures. Here we replicate the mean imputation method employed in Weinberg and Lamas (1993), modifying the approach to derive mean out-of-pocket costs to use mean expenditures computed directly from the analysis file underlying this study, rather than the published estimates from the unaged 1987 survey. Per capita MOOP amounts were computed by age and health insurance status and assigned to each person according to their values of the stratifying variables. Poverty status under the alternative method was computed at the family level by calculating family cash income less the family total amount of the imputed mean MOOP. Mean amounts used in this imputation model are available upon request.

Betson Imputation Model.

Betson (1995) proposed a clever two-stage imputation model to impute family-level MOOP costs from NMES to the March CPS, constrained to using information common to the March CPS (before March 1997) and NMES. The first stage stochastically assigned families to have nonzero MOOP costs based on age, insurance status, race, family size, and poverty status. The second stage imputed the amount of MOOP to those simulated to incur such costs. The equation used to predict expenditures was not estimated directly. Instead, Betson estimated a model predicting the log odds ratio as a function of the log of MOOP and demographic characteristics. He then transformed that equation, solving for expenses as a function of the log odds ratio and demographic characteristics. The theory was that since the odds ratio itself can be simulated based on a random draw, expenditures can be predicted as a function of the simulated log odds ratio and the characteristics of the population. The characteristics used in the second stage model were the same as those used to impute occurrence of MOOP costs in the first stage. The equation Betson specified and the transformation used to predict expenditures based on a simulated log odds ratio are:

A.1 LOGODDSRATIO = Bx + a*log(MOOP)
A.2 MOOP = exp((LOGODDSRATIO - Bx)/a)

For this study, we adapted the Betson model to impute MOOP to families and reestimated it based on NMES data aged to reflect the accounting period of the March 1992 CPS (demographic characteristics as of March and retrospective economic and expenditure information for the preceding calendar year). This yielded the Betson model, Option 1. In the original design, Betson estimated the log odds ratio based on aggregate data, using 9 intervals of expenditures to compute the cumulative distribution function. In our application of this model, we used the actual cumulative distribution function computed from the underlying data.(18) In other words, we ordered the data (within cells defined by the demographic characteristics) by MOOP costs from lowest nonzero value to highest. We then determined all unique values of expenditures and, for each value, computed the cumulative probability that an observation would have expenditures no larger than that value.(19) We then constructed the log odds ratio associated with each value of MOOP and estimated Betson's original equation using a weighted regression with normalized weights. Our coefficients are available upon request.

To impute expenditures to the data underlying this study we used this two-stage model with the transformed second stage equation, as did Betson. We used a random draw from a uniform distribution to determine if a family had expenses based on the probabilities derived directly from the NMES data (and available upon request). If a family was simulated to have expenses, we used a second random draw from a uniform distribution to compute the log odds ratio. We then calculated the log of expenditures as a function of the simulated log odds ratio, the estimated coefficients, and the characteristics of the family. The final expenses were computed as the antilog of that amount bounded at 1 on the low end and at the 99th percentile of reported expenses on the high end (8200 for Nonelderly and 18000 for elderly). The bounding of the results at the high end was necessary to bring the aggregate results in line with the target by controlling the size of the outliers. The unbounded model tended to generate values of expenditures so high for a small number of cases that the aggregate bottom line was noticeably affected.

Betson reestimated his model and shared the results with me (Betson model, Option 2). In so doing he made some refinements to the design and the estimation procedure. First, he adopted data on the detailed distribution of MOOP discussed above. Second, he expanded the set of "x" variables in equation A.1 to distinguish between public and private insurance among Nonelderly families. Third, he developed a model to predict the coefficient of log(MOOP) in equations A.1 and A.2.

Statistical Match.

To take advantage of the newly expanded information in SIPP, I designed a statistical match to impute MOOP as a function of medical service utilization, health and disability status, insurance coverage, demographics, and poverty status. The match was performed at the person rather than family level. The match consisted of recipients, i.e., persons to whom imputed data are assigned, and donors, i.e., persons from whom the expenditures were derived. The procedure to link donors and recipients included an exact match component and a statistical component:

- *Exact Match Component.* For a given recipient, potential donors were selected from among people who had the same value of the following variables: hospital utilization (yes or no), self-reported health status, insurance status, unit size, and disability status. This was the exact match component because all donors had to match recipients along these dimensions.

- *Statistical Component.* Among those potential donors, the actual donor was chosen to be the person who most closely matched the recipient on utilization of dental, physician service, or drug use, bed days, age, race, poverty status, and sex.[20] Closeness was defined by the minimizing the difference between the weighted sum of these variables from the donors and recipients. In the event of a tie, persons were chosen from among those who most closely resembled the recipient based on age. In the event of another tie, persons were chosen from among those who most closely resembled the recipient based on bed days. In the event of yet another tie, the chosen person had the closest value of family poverty ratio.

In this study, I impute MOOP to the NMES analysis file on which MOOP was reported. I used the same file as the potential donors in the match but constrained the approach to prevent an observation from matching to itself. Sample units and all their members within the analysis file were randomly assigned to one of two subsamples, Sample A and Sample B. Sample A formed the recipients for one match with Sample B forming the donors. Then Sample B formed the recipients for a second match with Sample A forming the donors. The enhanced Samples A and B were then concatenated to form a full analysis file with imputed as well as reported MOOP.

To explore the variation in the underlying imputed values, I replicated the sample draw using different random numbers and repeated the imputation process, thus generating 58 replicates analyzed in table 7. For each replicate, I compared the imputed MOOP to reported MOOP from the donor file. I also compared the imputed and reported amounts within the recipient file itself.

The weights used to select the best donor from among the potential donors could be altered to improve the imputation of MOOP. Thus, in addition to replicating the underlying samples, I also replicated the match altering the relative weights, generating 50 more replicates analyzed in table 7. The variations included equal weights to all factors, eliminating all but one factor (cycling through each factor), and keeping all factors but varying the relative importance of each item within the distance function. In the end the optimum weights essentially assigned a slightly higher weight (of 10) to utilization variables than to demographic variables (8), but no variation within each of those two groups.

FOOTNOTES

1. This paper reports the general results of research undertaken by the Census Bureau staff. The views expressed are attributable to the author and do not necessarily reflect the views of the Census Bureau or the U.S. Government.
2. This is a short term recommendation. SeeDoyle and Johantgen (1996) for longer term strategies.
3. Refer to Doyle, Beauregard and Lamas (1993) for the impact of MOOP after the other NAS changes were implemented.
4. Later in this paper (in the FINDINGS section) I present some statistics to illustrate the skewed nature of the distribution of MOOP.
5. As discussed below, I did not use a precise replicate of Betson's original model, opting instead to use two different versions of the Betson model are described in the appendix.

6. Based on an analysis of CPS data, the impact of Medicare part b on the alternate poverty rate is quite small, .1 percentage points overall and 1.3 percentage points among the elderly.
7. Detailed tables from the Consumer Expenditure Survey for years 1992 through 1995 U.S. Department of Labor, Bureau of Labor Statistics show some upward trend in out-of-pocket costs toward health insurance but do not show a clear trend among other categories of MOOP.
8. Studies of the marginal impact of each of the other components of the poverty measurement recommendations typically do not use adjusted thresholds. (See for example, Baugher and Lamison-White, 1996.) This makes sense for all aspects of the recommendations which do not fundamentally deviate from the original definition of poverty (i.e., those recommended changes which simply update the definition of income to reflect the increased reliance on taxes and in-kind benefits to provide assistance to those in need). However, the recommendation for the treatment of MOOP (as well as child care and work related expenses) represent a structural change in the definition of income and thus, I argue, should be evaluated in light of a correspondingly adjusted threshold.
9. Unlike the multiple imputation strategies for survey nonresponse proposed by Little and Rubin (1987), I propose the use of multiple imputation strategies in the context of identifying the best value to use for the parameters of the imputation model and to provide some estimate of the random variation associated with that model.
10. If I had used an unadjusted threshold, rather than one from which the MOOP component had been removed, then the increase in poverty would have been 1.7 percentage points instead of 0.8.
11. The poverty rates do not rise for all groups, as some reviewers of the this paper expected (see, for example, Medicaid-targeted groups, i.e., children and persons in female-headed families, who have on average low amounts of MOOP expenses). This is because the threshold was adjusted downward to remove the MOOP component, thus capturing the impact of Medicaid in reducing poverty.
12. Cohen, Cornelius, Hahn, and Levy (1994) indicate that 95 percent of medical expenses for Medicaid-covered children under 6 are paid by Medicaid as are 90 percent of expenditures for Medicaid-covered children ages 6 to 17.
13. Detailed tables from the Consumer Expenditure Survey for years 1992 through 1995 (U.S. Department of Labor, Bureau of Labor Statistics) do not show a discernable trend in MOOP among persons under age 25.
14. Calibration is a method of fine-tuning the results of an imputation model so that it replicates "truth". Of course, "truth" has to be estimated either from the data on which the imputation model is based or on information from an independent sources.
15. In this context I am not referring to the classic use of multiple imputation for imputation of nonresponse Little and Rubin, 1987). I am proposing to use it in a sensitivity analysis of alternate models for defining a statistical match.
16. As discussed in the Appendix, the weights applied to the distance function determine the ultimate choice of a donor with in cells defined for exact matches.
17. The order of magnitude of the mean values between the Betson and match replicates differs because the Betson replicate statistics are family based and the Match replicates are person based.
18. Originally, Betson was unable to replicate this approach because he did not have access to the microdata.
19. To make the model work, we excluded the highest value of MOOP costs within each cell and inserted an odds ratio of .999995/(1-.999995) associated with a value larger than the second highest.
20. Bed days refers to the number of days in bed for more than half a day due to illness or injury. This excludes days spent in the hospital.