Comparison of Imputation Adjustment Techniques on Variance Estimation in the Medical Expenditure Panel Survey (MEPS)[1]

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Abstract
The Medical Expenditure Panel Survey (MEPS) is a national probability sample survey designed to provide nationally representative estimates of health care use, expenditures, sources of payment, and insurance coverage for the U.S. civilian noninstitutionalized population. Depending on the type of medical event, there are varying levels of item nonresponse on medical expenses as collected in the MEPS household interview. MEPS also collects expenditure data in the Medical Provider Component (MPC) of the survey. Missing expenditure data for health care events are completed through a weighted sequential hot deck procedure with MPC data as the primary donor source. Studies in 2004, 2005, and 2008 examined the impact of imputation on estimates of variance for MEPS health care expenditures. This study updates this research by investigating fractionally weighted imputation as a method to reduce the impact of imputation on the actual variance of the estimates.

Key Words: Fractionally weighted imputation, variance estimation, Rao-Shao adjustment, survey data

1. Introduction

The Medical Expenditure Panel Survey (MEPS) collects data on health care utilization, expenditures, sources of payment, insurance coverage, and health care quality measures. The survey has been conducted annually since 1996 by the Agency for Healthcare Research and Quality (AHRQ) and is designed to produce national and regional estimates for the U.S. civilian noninstitutionalized population. MEPS collects health care expenditure data from both household respondents (Household Component – HC) and from a sample of their health care providers (Medical Provider Component – MPC). Health care expense data are collected at the event level for eight medical event types (e.g., office-based visits, hospital inpatient stays, etc.). While the amount of item nonresponse varies across the different medical event types, in general, there is substantial item nonresponse for the expenditure data in MEPS. When payment information is missing from either the household or medical provider components, the missing data are imputed at the event level using a weighted sequential hot-deck procedure (Cox, 1980).

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Under a valid nonresponse model a random hotdeck imputation procedure, such as the weighted sequential hotdeck, will produce quasi-randomization unbiased estimates. However, all imputation procedures in some way introduce extra variance into an estimate containing imputed data. The purpose of this study is to investigate fractionally weighted imputation as a method to ameliorate the increase in variance due to imputation.

2. Background

2.1 MEPS Overview

The MEPS-HC collects data from individual households and their members. These households come from a nationally representative subsample of households that participated in the prior year's National Health Interview Survey (NHIS) conducted by the National Center for Health Statistics. The NHIS sample is a stratified, multistage, probability proportional to size (pps) selection of households. For most years, the MEPS-HC sample comprises approximately 200 PSUs and covers approximately fifteen thousand households or about twenty-seven thousand persons. Using an overlapping panel design, the MEPS-HC collects data over a two and one-half year period covering a two year reference period through a series of five rounds of interviews. Details regarding the MEPS sample design as well as the construction of analytic weights can be found in Cohen (1997 & 2000) and Ezzati-Rice et al. (2008).

While the MEPS-HC collects data reflecting various facets of the U.S. health care system (e.g., utilization, insurance coverage, access to care, and quality) the primary intent of the survey is to collect data on health care expenditures. The survey facilitates analyses of distributions of health care expenditures and sources of payment, concentrations of expenditures, expenditures for specific health conditions, and trends in expenditures over time. The health care expenditure variables are the key analytic variables in MEPS and are highly policy relevant.

It is difficult to obtain complete expenditure information from household respondents. In an effort to reduce the level of item nonresponse for expenditures and to improve the accuracy of household reported data, the MEPS-MPC collects expenditure data from a sample of the survey participants' health care providers. However, for a significant proportion of medical events, expenses are not available from either survey source (i.e., MEPS-HC or MEPS-MPC), and the data are imputed. These missing data are currently imputed using the weighted sequential hotdeck proposed by Cox (1980). Machlin and Dougherty (2004) described how the weighted sequential hotdeck is applied to the MEPS expenditure data.

2.2 Previous Study Findings

Three previous studies have examined MEPS expenditure estimates and variance adjustment methods that account for the imputation's impact on the variance (Zodet et. al. 2008, Baskin et al. , 2004 & 2005). The impetus for these studies was the fact that most analyses of the MEPS expenditure data are performed using standard statistical software packages and assume that all the data values are observed. Treating all data values as observed does not reflect any potential variance introduced by the imputation procedure. Hence, the variance/standard error estimates reported from these analyses tend to be downwardly biased (i.e., too small).

To gauge the impact of the current weighted sequential hotdeck imputation on the variance estimates for MEPS expenditures, Baskin et al. (2004, 2005) compared two variance estimates that were derived ignoring imputation to two variance estimates that accounted for imputation. The two naïve variance estimates were derived using Taylor series expansion and balanced repeated replication (BRR). To generate variance estimates that accounted for the imputation the authors first used the BRR replicates and independently reimputed missing data within each replicate and for the full sample using the production software maintained by Westat. BRR estimates of variance were then generated which accounted for the added variance due to imputation. In addition, the authors used a modified BRR adjustment method developed by Rao and Shao (1999). The Rao-Shao adjustment is performed at the replicate level and only imputed data values are adjusted. The adjustment made to the imputed values amounts to the difference between the full sample mean and the corresponding replicate mean. These studies looked at both MEPS inpatient and outpatient expenditure data from 2001. Their findings suggested an approximate 30% increase in the estimated standard error (SE) when accounting for the imputation. Zodet et. al. (2008) used predictive mean matching and applied multiple imputation to the inpatient data to assess the variance due to imputation. For the predictive mean matching used in that study, the increase in variance was on the order of eight percent for total inpatient expenditures.

3. Methods

The objective of this study is to evaluate fractionally weighted imputation for generating MEPS expenditure estimates. Fractionally weighted imputation was introduced in Kalton and Kish (1984) as a methodology to improve the quality of imputations. Fractionally weighted imputation has been advocated in Fay (1996) and Kim and Fuller (2004). The idea of fractionally weighted imputation is relatively simple to implement and applies to any statistically valid imputation procedure. The imputation process is *replicated* a fixed number of times, say r times, where r is typically three to ten. Then each imputation is assigned a fractional weight that adds to one. The fractional weight is usually the reciprocal of r. A non-imputed observation would receive a fractional weight of one. These fractional weights are then multiplied times the survey weights in order to produce estimates. If the original imputation procedure is unbiased for linear functions of the data, then the fractionally weighted imputation will also be unbiased for linear functions of the data.

Note that the literature has used the term *multiple imputation* for a process of repeating *proper* imputations multiple times. These terms are defined in Rubin (1987). It is easy to see that for a proper imputation, both fractionally weighted imputation and multiple imputation, if performed the same number of times, would yield equal linear functions of the data. However, for non-linear functions of data such as medians, the point estimates from fractionally weighted imputation and multiple imputation will not necessarily agree.

3.1 Data

Data for this project are the same hospital inpatient facility events from 2001 that were examined previously by Zodet et. al. (2008) and Baskin et al. (2004, 2005). Hospital inpatient events are of particular interest for a number of reasons. First, these events represent a sizable proportion of overall health care expenditures: ≈29 percent. Second, inpatient expenditures are much more variable and more positively skewed than other types of medical event expenditures (e.g., office-based expenditures). Third, these data have a relatively large proportion of observations that require either full or partial imputation: ≈28 percent. Due to the resource intensive nature of creating an updated analytic file with current imputation classes, the decision was made to continue working with the 2001 data. Tabulations of more recent MEPS data suggest that the proportion of inpatient events requiring imputation has been consistent over the years.

3.2 Fractionally Weighted Imputation

Single random hotdeck imputation involves replacing missing values with values from the observed data. This assumes an implicit model for the nonresponse mechanism and requires that imputation cells are constructed based on the underlying response model. The quasi-randomization approach implies that the resulting estimate will be quasi-design unbiased if the underlying response model holds.

Fractionally weighted imputation replicates this imputation *r* times resulting in *r* imputed values for the missing data. Each non-imputed value is given a fractional weight of one and each imputed value is given a fractional weight of the reciprocal of *r*. Then each survey weight is multiplied by the fractional weight to produce an adjusted weight that is used in analysis.

The fractionally weighted estimate of total, for example, would then be given by the standard survey estimate (Equation 1).

$$\hat{\theta}_{total} = \sum_i \tilde{w}_i \tilde{Y}_i \quad where \begin{cases} \tilde{Y}_i = Y_i \; and \; \tilde{w}_i = w_i \; if \; Y_i \; is\, observed \\ \tilde{Y}_i \, is\, imputed \; and \; \tilde{w}_i = \dfrac{w_i}{r} \, if \; Y_i \; is\, not\; observed \end{cases}$$

Thus standard survey software can be used to produce point estimates and variance estimates for fractionally weighted imputed data.

3.3 Variance estimation in the presence of imputation

Standard analysis of complete datasets does not properly account for the increase in variance due to imputation of data. The previous studies of Zodet et. al. (2008) and Baskin et. al. (2004, 2005) have attempted to address this issue for MEPS imputed data using different methodologies. The current study will use the method of Rao-Shao for BRR estimates, from Rao and Shao (1999), which adjusts each replicate estimate to account for the imputation. This Rao-Shao adjustment can be used with fractionally weighted imputation, but there is no theory supporting the use of the Rao-Shao adjustment with the weighted sequential hotdeck. For this reason a true pps weighted hotdeck was substituted for the weighted sequential hotdeck in this study. Note that Rao and Shao (1999) does directly address the use of a true pps hotdeck in conjunction with the Rao-Shao adjustment.

The true pps hotdeck should be first order equivalent to the weighted sequential hotdeck, i.e, the two procedures should produce equivalent point estimates. However, the second order properties of the weighted sequential hotdeck are intractable. There is little to relate the second order properties of the weighted sequential hotdeck to a true pps hotdeck, but simulation studies such as Andridge and Little (2009) indicate that the weighted sequential hot deck may have smaller variance than a true pps hotdeck.

4. Results

Table 1 presents the naïve estimate of the variance of mean hospital inpatient expenditures for a single imputation and various repeated imputations. For the naïve estimate of variance, which does not properly account for the increase in variance due to imputation, the decrease in variance due to having three repeated imputations is thirteen percentage points, and with ten repeated imputations the decrease in variance is seventeen percentage points. Although these estimates do ignore the increase in variance due to imputation, it does represent the magnitude of decrease in variance that an end user would see in their estimates.

Table 1. Naïve variance of mean hospital inpatient expenditures per event (FWI denotes a fractionally weighted estimate)

	Single Impute	FWI-3 times	FWI-5 times	FWI-7 times	FWI-10 times
Naïve Variance	61,464	53,657	52,077	51,398	50,886
% of Single Impute	100%	87%	85%	84%	83%

Source: MEPS hospital inpatient facility event data, 2001 (not official public release data)

Table 2 presents the Rao-Shao adjusted variance of mean hospital inpatient expenditures for a single imputation and various repeated imputations. For the Rao-Shao adjusted estimate of variance, the decrease in variance due to having three repeated imputations is three percentage points, and with ten repeated imputations the decrease in variance is five percentage points. These estimates represent the magnitude of actual decrease in variance under a true pps random hotdeck. The estimates are quite large in comparison to the naïve estimate and indicate that much more testing of this process is necessary before these results can be considered to be accurate. However, the actual decrease in variance due to using a fractionally weighted imputation is certainly non-negligible.

Table 2. Rao-Shao adjusted variance of mean hospital inpatient expenditures per event (FWI denotes a fractionally weighted estimate)

	Single Impute	FWI-3 times	FWI-5 times	FWI-7 times	FWI-10 times
BRR Adjusted	234,562	226,741	225,162	224,481	223,967
% of Single Impute	100%	97%	96%	96%	95%

Source: MEPS hospital inpatient facility event data, 2001 (not official public release data)

5. Conclusions

By evaluating a different imputation method, weighted random imputation, indirect evidence suggests that fractionally weighted imputation using the current production method of weighted sequential hotdeck may provide a reduction in variance of hospital inpatient facility expenditures of approximately five percent. If this reduction extends to all of the imputation performed in MEPS, it would be a relatively cost effective method of reducing the overall variance of an important national estimate. However, the evaluation of other imputations needs to be conducted at a future date to corroborate this result.

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