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Tools for analyzing multiple imputed datasets

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Abstract. The method of multiple imputation (MI) is used increasingly for analyzing datasets with missing observations. Two sets of tasks are required in order to implement the method: (a) generating multiple complete datasets in which missing values have been imputed by simulating from an appropriate probability distribution and (b) analyzing the multiple imputed datasets and combining complete data inferences from them to form an overall inference for parameters of interest. An increasing number of software tools are available for task (a), although this is difficult to automate, because the method of imputation should depend on the context and available covariate data. When the quantity of missing data is not great, the sensitivity of results to the imputation model may be relatively low. In this context, software tools that enable task (b) to be performed with similar ease to the analysis of a single dataset should facilitate the wider use of multiple imputation. Such tools need not only to implement techniques for inference from multiple imputed datasets but also to allow standard manipulations such as transformation and recoding of variables. In this article, we describe a set of Stata commands that we have developed for manipulating and analyzing multiple datasets.

Keywords: st0042, missing data, multiple imputation, Rubin’s rule of combination, overall estimates

1 Introduction

The presence of missing data is a frequent source of difficulties in statistical practice. In large surveys, subjects may decline to participate or fail to respond to particular items in a questionnaire. The situation may be worse in longitudinal studies where investigators seek participation from individuals over several occasions—subjects may decline to respond to certain questions at each occasion (“item missingness”) or fail to participate entirely at some occasions (“occasion missingness”).

A simple way to deal with incompletely observed data is to omit any case that has a missing value for any variables required in the analysis of interest. This so-called complete-case analysis may, however, produce biased inferences when the subgroup with complete data differs systematically from the target population. It may also lead to inefficient use of the collected information, since the number of individuals with complete data may be substantially less than the total sample size.
A slightly more sophisticated approach is to use single imputation, where missing values in a variable are simply filled in by a plausible estimate, such as the mean or median for that variable on other participants. Better estimates may be obtained by using the predicted means from a regression model or a hotdeck procedure (Little and Rubin 1987). Relative to the complete-case approach, single imputation has the advantage of retaining the full sample size, and in some situations, it can produce unbiased estimates of target parameters. It cannot, however, provide valid standard errors and confidence intervals, as it ignores the uncertainty implicit in the fact that the imputed values are not the actual values.

Under certain assumptions, valid inferences can, however, be obtained with the more sophisticated technique of multiple imputation introduced by Rubin (1987). The heuristic basis of this approach is that if several different complete datasets (rather than just one) are obtained by imputing missing values, appropriate account can be taken of the uncertainty involved in imputing the missing values by examining the variation between inferences obtained in each of the completed datasets. In practice, the statistician (not necessarily the same analyst who will make final substantive analyses of the data) produces several complete datasets using plausible modeling assumptions. The data analyst then analyzes each of these using standard complete-data methods, and then combines the results according to appropriate rules to produce overall estimates with confidence intervals and p-values. The overall estimates incorporate the missing-data uncertainty as well as sampling variation.

The key assumption with the method of multiple imputation, as with most approaches to missing data problems, is that the missing data are missing at random (MAR) in the sense that the probability of a value being missing may only depend on observed data for the individual in question and not on the unobserved missing values. The original formal definition of MAR was provided by Rubin (1976); Little and Rubin (1987) and Schafer (1997) provide more recent discussions. An essential requirement for the MI method to work in practice is that imputation should be performed under a model that is general enough to make the MAR assumption defensible, even if this model uses variables that are not of substantive interest for later data analysis.

Generating proper imputations for missing values in a given dataset is not straightforward. The general principle is that missing values should be imputed by simulation from their posterior predictive distribution under a plausible model fitted to the observed data. For general model specifications, this in principle requires Markov Chain Monte Carlo (MCMC) methods, and Schafer (1997) has developed a set of reasonably flexible software that covers a range of models. Imputation under a multivariate normal model for all variables (both those to be imputed and others used because of their association with the variable requiring imputation) is also now available in the S-PLUS and SAS packages. Another widely available tool is the SOLAS package (Statistical Solutions Ltd.), which implements an imputation method that provides considerable flexibility. It gives proper imputations when the pattern of missingness is monotone (variables can be arranged in order from those with least missing values to those with most) and otherwise employs pragmatic methods to force the data into a monotone missingness pattern. Raghunathan et al. (2001) have recently proposed another more flexible ap-
proach using conditional distributions and a SAS program is available to implement this. Finally, for small quantities of missing data, the approximate Bayesian bootstrap method implemented as the hotdeck command by Mander and Clayton (1999) may be adequate.

When you implement MI, it is usually sufficient to obtain a relatively small number of imputed datasets, often as few as 3 or 5, because the relative gains in precision from using larger numbers are minor, unless the fraction of missing data is extremely large (in which case the MAR assumption becomes increasingly tenuous in any case). See Rubin (1987) for details.

2 Statistical inference from multiple imputed datasets

The Stata commands presented in this article have been written to provide a large number of useful data manipulations and transformations simultaneously on multiple imputed datasets, enabling data analysts to have maximum flexibility in their analyses. Ultimately, the analyst will need to perform inferences using the multiple datasets, so we have implemented the simple method derived by Rubin (1987).

Suppose that initially our primary interest lies in a scalar estimand \( Q \). In a typical case, this might be a regression coefficient, for example, the log odds ratio in a logistic regression. Suppose that we have imputed \( m \) complete datasets using an appropriate model. In each of these datasets, we use standard complete-data methods to obtain an estimate of \( Q \) with an associated estimated variance (or equivalently, standard error). Let \( \hat{Q}^{(k)} \) and \( U^{(k)} \) denote the point estimate and variance respectively from the \( k \)th \((k = 1, 2, \ldots, m) \) dataset.

As might be expected, the multiple imputation point estimate of \( Q \) is the average of the \( m \) complete-data estimates:

\[
\bar{Q} = \frac{1}{m} \sum_{t=1}^{m} \hat{Q}^{(t)}
\]

Obtaining a valid standard error for this estimate requires combining information on within-imputation and between-imputation variation. The latter is important in reflecting variability due to imputation uncertainty.

First, a within-imputation variance component is obtained as the average of the complete-data variance estimates:

\[
W = \frac{1}{m} \sum_{t=1}^{m} U^{(t)}
\]
Second, between-imputation variance is calculated by a simple empirical combination of the complete-data point estimates:

\[ B = \frac{1}{m-1} \sum_{t=1}^{m} (\hat{Q}^{(t)} - \bar{Q})^2 \]

The total variance in the combined estimate of \( Q \) is then given by

\[ T = W + \left( 1 + \frac{1}{m} \right) B \]

and Rubin (1987) shows that, approximately,

\[ T^{-1/2}(Q - \bar{Q}) \sim t_\gamma \]

where the degrees of freedom \( \gamma \) are given by

\[ \gamma = (m - 1) \left\{ 1 + \frac{W}{(1 + 1/m)B} \right\}^2 \]

In the usual way, a 100(1 - \( \alpha \))% interval estimate for \( Q \) is

\[ \bar{Q} \pm t_{\gamma,1-\alpha/2} \sqrt{T} \]

The \((1 + 1/m)\) term in these simple equations indicates why it is not necessary to create a large number of imputed datasets, especially if there is a low ratio of between-imputation to within-imputation variance. The latter is typically the case unless there is a large fraction of missing data, along with relatively precise estimation of parameters within each dataset.

On occasion, it is of interest to perform inference for a multidimensional (vector) quantity, for example, when assessing a batch of effects related to a multi-category factor or examining interaction terms in a regression model. The simple methods described above for scalar estimands do not generalize immediately, but we have implemented an approximate method given by Li, Raghunathan, and Rubin (1991) to give a p-value for the null hypothesis that all components of a vector \( Q \) are equal to zero. Schafer (1997) cautions that for the procedure to work well, you should have a large sample and make sure that the scale in which \( Q \) is expressed is such that the usual normal-theory inferences for complete data are valid.

3 Syntax

\texttt{miset [ using filename-prefix ] [, mims(\#) clear]}

\texttt{mireset}
Tools for multiple imputed datasets

\texttt{miappend using filename-prefix [, nolabel keep(varlist)]}

\texttt{mimerge [varlist] using filename-prefix [, keep(varlist) unique uniqmaster uniqusing nolabel nokeep _merge(varname)]}

\texttt{misave filename-prefix [, replace]}

\texttt{mido Stata-command}

\texttt{mici [, indiv] : varlist [in range] [if exp] [, level(#) binomial poisson exposure(varname)]}

\texttt{mifit [, indiv] : [xi :] estimation command}

\texttt{milincom [, indiv] : exp [in range] [if exp] [, level(#) or irr eform]}

\texttt{mitestparm varlist}

where \textit{estimation command} may be \texttt{regress}, \texttt{logit}, \texttt{probit}, \texttt{clogit}, \texttt{glm}, \texttt{logistic}, \texttt{poisson}, \texttt{svyreg}, \texttt{svylogit}, \texttt{svyprobit}, \texttt{svypoisson}, \texttt{xtgee}, or \texttt{xtreg} followed by standard arguments and options for that command.

where \textit{exp} is any linear combination of coefficients that is valid syntax for \texttt{test}. Note that \textit{exp} must not contain an equal sign (see \texttt{[R lincom]}).

4 Description

\texttt{miset} creates temporary copies of imputed datasets so that subsequent \texttt{mi} (multiple imputation) commands can be executed on these data. The other \texttt{mi} commands can only be used after the multiple datasets have been declared by \texttt{miset}. The imputed datasets are assumed to be created from an original dataset by a “proper” imputation method. These datasets must each have the same variables and the same number of observations.

The following naming convention must be used: filenames of the imputed datasets must consist of a common word followed by a consecutive number, followed by the normal extension .dta; for example, \texttt{foo1.dta}, \texttt{foo2.dta}, \ldots, \texttt{foo5.dta}. Only the common word or \textit{filename-prefix} (“foo” in this case) is to be specified after the \texttt{using} command.
miset creates temporary files _mitemp1.dta, _mitemp2.dta, and so on by copying the using files. All subsequent commands will be executed on these temporary files, leaving the original using files unchanged. The temporary files remain in the working directory until mireset is issued. To save the updated temporary files after a series of mi commands, see misave.

mireset erases the temporary files created by miset and clears the global macros created by miset.

misave saves the multiple temporary datasets declared by the last miset with any subsequent changes made with the mi commands. File names are constructed from the filename-prefix followed by the numbers 1, 2, ..., m.

mido executes a Stata command on each of the datasets created by miset. Most commands can be used, except estimation and post-estimation commands. You cannot define value labels with mido. For execution of estimation-class commands with a combination of results over imputed datasets, see mifit; for post-estimation inferences, see milincom and mitestparm; and for manipulation of multiple datasets, see mimerge, miappend, and misave.

miappend appends the multiple datasets of the using files to the currently loaded miset datasets. The first using file is appended to the first miset file, the second to the second, and so on. The number of using datasets must be the same as the number of datasets declared in miset.

mimerge merges each of the miset datasets with each of the using datasets. The number of using datasets must be the same as that of the master datasets.

mici calculates confidence intervals separately for each of the miset datasets and calculates overall confidence intervals by Rubin's rule of combination (see section 2).

mifit carries out the estimation command on each of the miset datasets and then computes multiple-imputation point estimates of the regression parameters and associated overall variance estimates using Rubin's rule. Confidence intervals for the estimated model parameters are given. The xi prefix command can be used in the usual way within mifit to create dummy variables and interaction terms.

milincom computes multiple-imputation point estimates, standard errors, confidence intervals, t statistics, and p-values for linear combinations of regression coefficients after mifit using Rubin's combining rule (1). Results can be displayed optionally in exponentiated form (giving odds ratios or incidence rate ratios in appropriate circumstances).

mitestparm is the mi version of the post-estimation command testparm. It obtains an approximate F-test (Li, Raghunathan, and Rubin 1991) to test the hypothesis that the specified coefficients are all equal to zero, analogous to the standard Wald test.
5 Options

In general, commands inherit the standard Stata options for their parent command. Most options and prefixes are acceptable with mido; for example, mido by w: tab x y, sum(z) freq is a legal syntax. However, the parent options update and replace are not options for mimerge because these options take effect only when there are missing values in the master file, which should not occur with multiple imputed datasets. mifit accepts all options available in the estimation command.

5.1 Options for miset

mims(\#) specifies the number, \(m\), of datasets to be used. The default is 5. A minimum of 2 and a maximum of 9 datasets can be specified. If there are more than \(m\) datasets, only the first \(m\) datasets are used. As mentioned earlier, usually as few as 3 or 5 multiple imputed datasets is sufficient.

clear permits the data to be loaded, even if there is a dataset already in memory and if that dataset has changed since the data were last saved.

5.2 Options for miappend

nolabel prevents copying the value label definitions from the using dataset.

keep(varlist) specifies the variables to be kept from the using data. If keep() is not specified, all variables are kept.

These options are inherited from the parent command append.

5.3 Options for mimerge

keep(varlist) specifies the variables to be kept from the using data. If keep() is not specified, all variables are kept.

unique, uniquemaster, and uniquusing specify that the match variables in a match-merge uniquely identify the observations. See [R] merge for details.

nolabel prevents Stata from copying the value label definitions from the using dataset.

nokeep causes merge to ignore observations in the using data that have no corresponding observation in the master.

_merge(varname) specifies the name of the variable that will mark the source of the resulting observation. The default is _merge(_merge).

These options are all inherited from the parent merge command.
5.4 Option for misave

replace permits misave to overwrite existing datasets.

5.5 Options for mici

indiv reports the confidence intervals from each of the individual miset datasets, as well as the overall confidence intervals. By default, only the overall confidence interval is displayed.

level specifies the desired level of significance in calculating the confidence intervals. The default is to use the current system value defined by set level (whose initial value is 95%).

binomial specifies that each of the variables in varlist has a binomial distribution and that mici will calculate the binomial standard error for each of the miset datasets and then calculate an overall confidence interval for the corresponding proportion using Rubin’s combining rule. If any variable in varlist is not binary (value 0 or 1), an error message is given. Note that the “exact” binomial method is not used since it does not enable application of Rubin’s rule.

poisson specifies that the variables are Poisson-distributed counts. Poisson standard errors are calculated from individual miset datasets, and overall confidence intervals are computed using Rubin’s rule.

exposure(varname) is used only with poisson. varname contains the total exposure during which the number of events recorded in varlist was observed.

5.6 Options for mifit

indiv causes an estimation result to be output for each of the miset datasets. The default is that only overall estimation results are displayed.

In principle, any options of the original estimation command can be passed along to mifit.

5.7 Options for milincom

indiv causes milincom to report estimates of the linear combination obtained from each of the miset datasets, as well as an overall estimate obtained by the combining rule.

level(#) specifies the confidence level, as a percentage, for confidence intervals; see [R] level.

or, irr, and eform all report coefficient estimates as exp(b) rather than b. Standard errors and confidence intervals are similarly transformed. or is the default after logistic. The only difference in these options is how the output is labeled; see [R] lincom.
5.8 Options for mitestparm

The `testparm` options `equal` and `equation` have not yet been implemented.

6 Examples

We illustrate the `mi` commands using two sets of datasets: `smiF1.dta, ..., smiF5.dta` and `smiM1.dta, ..., smiM5.dta`. The datasets were imputed separately for gender, using a multivariate linear mixed effects model from data that contained 25% to 47% missing observations across variables. The data are extracted from a cohort study of adolescent health and consist mainly of self-reported indicators of substance use and other behavioral outcomes over 6 timepoints (waves), along with some fixed covariates.

First, we load the females’ datasets `smiF*.dta`:

```
. miset using smiF
smiF1.dta to smiF5.dta were loaded to _mitemp1.dta to _mitemp5.dta respectively
```

The five datasets have now been set up for `mi` operation. Note that the first dataset is always the one currently in memory after any `mi` command.

```
. describe
Contains data from _mitemp1.dta
obs: 600 Imputed females data No.1
vars: 10 11 Jun 2003 10:16
size: 10,200 (99.9% of memory free) (_dta has notes)

storage display value
variable name type format label variable label
id long %9.0g
wave byte %9.0g wave 1 to wave 6
mmetro byte %9.0g school in mmetro
parsmk byte %9.0g either parent smokes
drkfre byte %6.0g drkfre drink frequency
alcdos byte %6.0g alcday>=5 units at least once
alcdhi byte %6.0g alcday>=5 units at least once
smk byte %6.0g smk
 cis total score (0,56)
mkrflre byte %9.0g mis missing drkfre

Sorted by:  id wave
```

With a view to appending the males’ data, we generate a variable `sex=1` for females

```
. mido gen byte sex=1

-> Applying gen to dataset1 (_mitemp1.dta).
-> Applying gen to dataset2 (_mitemp2.dta).
-> Applying gen to dataset3 (_mitemp3.dta).
-> Applying gen to dataset4 (_mitemp4.dta).
-> Applying gen to dataset5 (_mitemp5.dta).
```
and we save the five datasets by issuing

```
    . misave temp, replace
    file temp1.dta saved
    file temp2.dta saved
    file temp3.dta saved
    file temp4.dta saved
    file temp5.dta saved
```

Similarly, we set up the males’ datasets and generate a variable \texttt{sex=0}.

```
    . miset using smiM
    smiM1.dta to smiM5.dta were loaded to _mitemp1.dta to _mitemp5.dta respectively
    . mido gen byte sex=0
    -> Applying gen to dataset1 (_mitemp1.dta).
    -> Applying gen to dataset2 (_mitemp2.dta).
    -> Applying gen to dataset3 (_mitemp3.dta).
    -> Applying gen to dataset4 (_mitemp4.dta).
    -> Applying gen to dataset5 (_mitemp5.dta).
```

We may then join the two datasets into a single one by appending \texttt{smiF1.dta} to \texttt{smiM1.dta}, \texttt{smiF2.dta} to \texttt{smiM2.dta}, and so on to form new datasets \texttt{both1.dta}, \texttt{both2.dat}, and so on.

```
    . miappend using temp
    . mido label data "male & female"
    -> Applying label to dataset1 (_mitemp1.dta).
    -> Applying label to dataset2 (_mitemp2.dta).
    -> Applying label to dataset3 (_mitemp3.dta).
    -> Applying label to dataset4 (_mitemp4.dta).
    -> Applying label to dataset5 (_mitemp5.dta).
    . qui mido labsex
    . mido sort id wave
    -> Applying sort to dataset1 (_mitemp1.dta).
    -> Applying sort to dataset2 (_mitemp2.dta).
    -> Applying sort to dataset3 (_mitemp3.dta).
    -> Applying sort to dataset4 (_mitemp4.dta).
    -> Applying sort to dataset5 (_mitemp5.dta).
    . misave both, replace
    file both1.dta saved
    file both2.dta saved
    file both3.dta saved
    file both4.dta saved
    file both5.dta saved
```

Note that in the above, the values of \texttt{sex} were labeled by calling a user-written program \texttt{labsex} using \texttt{mido}. \texttt{labsex} was defined by an ado-file as follows:
As Stata does not differentiate between built-in and ado-defined commands, `mido` also accepts commands defined by ado-files.

Now, we base our analysis on the datasets both. The variable `mdrkfre` is an index equal to 1 if `drkfre` was missing in the original data (before imputation), and zero otherwise. So, `mdrkfre=0` corresponds to actual observations and `mdrkfre=1` corresponds to imputed observations. We see that there are a total of 163 observations missing in `drkfre`. These missing values are filled in differently in the five datasets, as shown in column two of the following tables.

```
. miset using both
both1.dta to both5.dta were loaded to _mitemp1.dta to _mitemp5.dta respectively
. mido tab drkfre mdrkfre

-> Applying tab to dataset1 (_mitemp1.dta).

<table>
<thead>
<tr>
<th>drink frequency</th>
<th>missing drkfre</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non drinker</td>
<td>438</td>
<td>51</td>
</tr>
<tr>
<td>not in last wk</td>
<td>326</td>
<td>69</td>
</tr>
<tr>
<td>&lt;3 days last wk</td>
<td>203</td>
<td>36</td>
</tr>
<tr>
<td>&gt;=3 days last wk</td>
<td>40</td>
<td>7</td>
</tr>
<tr>
<td>Total</td>
<td>1,007</td>
<td>163</td>
</tr>
</tbody>
</table>

-> Applying tab to dataset2 (_mitemp2.dta).

<table>
<thead>
<tr>
<th>drink frequency</th>
<th>missing drkfre</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non drinker</td>
<td>438</td>
<td>44</td>
</tr>
<tr>
<td>not in last wk</td>
<td>326</td>
<td>69</td>
</tr>
<tr>
<td>&lt;3 days last wk</td>
<td>203</td>
<td>38</td>
</tr>
<tr>
<td>&gt;=3 days last wk</td>
<td>40</td>
<td>12</td>
</tr>
<tr>
<td>Total</td>
<td>1,007</td>
<td>163</td>
</tr>
</tbody>
</table>

-> Applying tab to dataset3 (_mitemp3.dta).

<table>
<thead>
<tr>
<th>drink frequency</th>
<th>missing drkfre</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non drinker</td>
<td>438</td>
<td>49</td>
</tr>
<tr>
<td>not in last wk</td>
<td>326</td>
<td>70</td>
</tr>
<tr>
<td>&lt;3 days last wk</td>
<td>203</td>
<td>37</td>
</tr>
<tr>
<td>&gt;=3 days last wk</td>
<td>40</td>
<td>7</td>
</tr>
<tr>
<td>Total</td>
<td>1,007</td>
<td>163</td>
</tr>
</tbody>
</table>
```
Suppose that we are interested in the risk of drinking on a regular (at least weekly) basis. We may recode the variable `drkfre` in each dataset to a binary indicator and obtain the frequency of this level of drinking at each `wave` as follows.

```
. mido gen drkreg = drkfre>=2
```

```
> Applying gen to dataset1 (_mitemp1.dta).
> Applying gen to dataset2 (_mitemp2.dta).
> Applying gen to dataset3 (_mitemp3.dta).
> Applying gen to dataset4 (_mitemp4.dta).
> Applying gen to dataset5 (_mitemp5.dta).
> for num 1/6: mici: drkreg if wave==X, bin
> mici: drkreg if wave==1, bin (male & female)
```

| Overall estimates -- Binomial -- |
|-------------------------------|----|-----------------|-----------------|
| Variable | Obs | Mean  | Std. Err. | [95% Conf. Interval] |
| drkreg   | 195 | .1230769 | .0238581 | .0763051 .1698487 |

```
> mici: drkreg if wave==2, bin (male & female)
```

| Overall estimates -- Binomial -- |
|-------------------------------|----|-----------------|-----------------|
| Variable | Obs | Mean  | Std. Err. | [95% Conf. Interval] |
| drkreg   | 195 | .2061539 | .0309131 | .1452904 .2670173 |

```
> mici: drkreg if wave==3, bin (male & female)
```

| Overall estimates -- Binomial -- |
|-------------------------------|----|-----------------|-----------------|
| Variable | Obs | Mean  | Std. Err. | [95% Conf. Interval] |
| drkreg   | 195 | .2444026 | .0328858 | .1793391 .308866 |
Tools for multiple imputed datasets

-> mici: drkreg if wave==4, bin
    (male & female)
    Overall estimates
    | Variable | Obs | Mean     | Std. Err. | [95% Conf. Interval] |
    |----------|-----|----------|-----------|---------------------|
    | drkreg   | 195 | 0.2912821| 0.035184  | 0.2218792 - 0.3606849|

-> mici: drkreg if wave==5, bin
    (male & female)
    Overall estimates
    | Variable | Obs | Mean     | Std. Err. | [95% Conf. Interval] |
    |----------|-----|----------|-----------|---------------------|
    | drkreg   | 195 | 0.2646154| 0.0338951 | 0.1978309 - 0.3313999|

-> mici: drkreg if wave==6, bin
    (male & female)
    Overall estimates
    | Variable | Obs | Mean     | Std. Err. | [95% Conf. Interval] |
    |----------|-----|----------|-----------|---------------------|
    | drkreg   | 195 | 0.3558975| 0.0407032 | 0.2740175 - 0.4377774|

Examining the wave 6 outcome in more detail, the indiv results reveal a moderate amount of between-imputation variability, resulting in an overall SE about 20% greater than the apparent SE within each imputed dataset.

. mici, indiv : drkreg if wave==6, bin
    (male & female)
    Variable
    | Data   | Obs | Mean     | Std. Err. | [95% Conf. Interval] |
    |--------|-----|----------|-----------|---------------------|
    | drkreg | 195 | 0.348718 | 0.0341275 | 0.2818293 - 0.4156066|
    | _mitemp1 | 195 | 0.3435898| 0.0340087 | 0.2769338 - 0.4102456|
    | _mitemp2 | 195 | 0.3333333| 0.033758 | 0.2671689 - 0.3994977|
    | _mitemp3 | 195 | 0.3794872| 0.0347501 | 0.3113782 - 0.4475962|
    | _mitemp4 | 195 | 0.374359 | 0.0346569 | 0.3064328 - 0.422852|
    | _mitemp5 | 195 | 0.3558976| 0.0407032 | 0.2740175 - 0.4377774|
    | Overall  | 195 | 0.3558975| 0.0407032 | 0.2740175 - 0.4377774|

There is a clear trend for the prevalence of regular drinking to increase with wave, and we may use logistic regression to examine whether this trend is similar for males and females. Note the use of the option cluster(id) to obtain robust standard errors allowing for within-subject correlation.

. mifit : xi: logistic drkreg i.sex*wave, cl(id)

    Overall estimates
    Number of obs  =    1170

    |            | Odds Ratio | Std. Err. | t  | P>|t| | [95% Conf. Interval] | MI.df |
    |-------------|------------|-----------|----|------|----------------------|-------|
    | _Isex_1     | 0.52254    | 0.20336   | -1.67 | 0.095 | 0.24369 - 1.1205     | 66938.36 |
    | wave        | 1.2254     | 0.07173   | 3.47 | 0.001 | 1.0921 - 1.375       | 308.41  |
    | _IsexWave_1 | 1.038      | 0.08448   | 0.46 | 0.647 | 0.88467 - 1.2178     | 681.17  |
Next, we assess potential nonlinearity (in the logistic scale) by including in the model a (centered) quadratic term in \textit{wave}.

\begin{verbatim}
. mido gen wave2 = (wave-2.5)^2
  \rightarrow Applying gen to dataset1 (_mitemp1.dta).
  \rightarrow Applying gen to dataset2 (_mitemp2.dta).
  \rightarrow Applying gen to dataset3 (_mitemp3.dta).
  \rightarrow Applying gen to dataset4 (_mitemp4.dta).
  \rightarrow Applying gen to dataset5 (_mitemp5.dta).
. mifit: logistic drkreg sex wave wave2, cl(id)
\end{verbatim}

\begin{verbatim}
Overall estimates
Number of obs  =  1170

| drkreg | Odds Ratio | Std. Err. | t    | P>|t| | [95% Conf. Interval] | MI.df |
|--------|------------|-----------|------|------|-----------------------|-------|
| sex    | 0.60251    | 0.14386   | -2.12| 0.035| 0.37667 - 0.96374     | 323.55|
| wave   | 1.3483     | 0.09245   | 4.36 | 0.000| 1.1786 - 1.5425       | 1036.19|
| wave2  | 0.9656     | 0.02415   | -1.40| 0.167| 0.91844 - 1.0152      | 57.74 |
\end{verbatim}

Slightly more precise estimates can be obtained using the GEE method (with the default assumption of exchangeable working correlations).

\begin{verbatim}
. mifit: xtgee drkreg sex wave, fam(binom) i(id) eform
\end{verbatim}

\begin{verbatim}
Overall estimates
Number of obs  =  1170

| drkreg | Odds Ratio | Std. Err. | t    | P>|t| | [95% Conf. Interval] | MI.df |
|--------|------------|-----------|------|------|-----------------------|-------|
| sex    | 0.6102     | 0.14544   | -2.07| 0.039| 0.38139 - 0.97629     | 202.30|
| wave   | 1.2457     | 0.04823   | 5.67 | 0.000| 1.1535 - 1.3454       | 87.39 |
\end{verbatim}

It may also be of interest to examine the association with other covariates; for example, a measure of psychological morbidity grouped into 3 categories:

\begin{verbatim}
. mido gen cisgp = cistot
  \rightarrow Applying gen to dataset1 (_mitemp1.dta).
  \rightarrow Applying gen to dataset2 (_mitemp2.dta).
  \rightarrow Applying gen to dataset3 (_mitemp3.dta).
  \rightarrow Applying gen to dataset4 (_mitemp4.dta).
  \rightarrow Applying gen to dataset5 (_mitemp5.dta).
. mido recode cisgp 0/5=1 6/11=2 12/100=3
  \rightarrow Applying recode to dataset1 (_mitemp1.dta).
  \rightarrow Applying recode to dataset2 (_mitemp2.dta).
  \rightarrow Applying recode to dataset3 (_mitemp3.dta).
  \rightarrow Applying recode to dataset4 (_mitemp4.dta).
  \rightarrow Applying recode to dataset5 (_mitemp5.dta).
\end{verbatim}
-> Applying recode to dataset5 (_mitemp5.dta).
(cisgp: 1076 changes made)

. mifit: xi: xtgee drkreg sex wave i.cisgp, fam(binom) i(id) eform

Overall estimates

| drkreg | Odds Ratio | Std. Err. | t     | P>|t| | [95% Conf. Interval] | MI.df |
|--------|------------|-----------|-------|------|----------------------|-------|
| sex    | 0.55838    | 0.13396   | -2.43 | 0.016 | 0.34826 to 0.89529   | 303.65|
| wave   | 1.2807     | 0.05258   | 6.03  | 0.000 | 1.1802 to 1.3897     | 81.89 |
| _Icisgp_2 | 1.0057     | 0.19269   | 0.03  | 0.976 | 0.68955 to 1.4668     | 241.80|
| _Icisgp_3 | 1.7755     | 0.35374   | 2.88  | 0.004 | 1.2 to 2.8572        | 358.64|

A test of the overall null hypothesis of no differences between the three “CIS groups” can be obtained using the `mitestparm` command:

. mitestparm _Icis*
   (1) _Icisgp_2 = 0
   (2) _Icisgp_3 = 0
   F( 2, 3996) = 5.45
   Prob > F = 0.0043

There is clearly strong evidence against the null hypothesis—not surprising, given the individual effect estimates in the regression table, which reveal that this is entirely due to an elevated odds in the third group.

Although there was no evidence of `sex` by `wave` interaction, we refit this model to illustrate the use of `milincom`.

. mifit: xi: logistic drkreg i.sex*wave

Overall estimates

| drkreg | Odds Ratio | Std. Err. | t     | P>|t| | [95% Conf. Interval] | MI.df |
|--------|------------|-----------|-------|------|----------------------|-------|
| _Isex_1 | 0.52254    | 0.18247   | -1.86 | 0.063 | 0.26356 to 1.036     | 43384.52|
| wave   | 1.2254     | 0.07201   | 3.46  | 0.001 | 1.0916 to 1.3756     | 313.20 |
| _IsexWave_1 | 1.038     | 0.08936   | 0.43  | 0.665 | 0.87658 to 1.229     | 852.87|

. milincom: wave + _IsexXwave_1

Overall estimates

| drkreg | Odds Ratio | Std. Err. | t     | P>|t| | [95% Conf. Interval] | MI.df |
|--------|------------|-----------|-------|------|----------------------|-------|
| (1)    | 1.271952   | 0.083788  | 3.65  | 0.000 | 1.117311 to 1.447996  | 303.59|

This provides an estimate of the OR per wave among females; as the interaction term is very small, this is almost identical to that among males (1.2254).
Now, we reshape the data to examine longitudinal changes in more detail; for example, below examining the uptake of drinking between waves 1 and 2.

```
. mido gen drkany = drkfre≥1
-> Applying gen to dataset1 (_mitemp1.dta).
-> Applying gen to dataset2 (_mitemp2.dta).
-> Applying gen to dataset3 (_mitemp3.dta).
-> Applying gen to dataset4 (_mitemp4.dta).
-> Applying gen to dataset5 (_mitemp5.dta).
. mido keep id wave drkany cisgp sex
-> Applying keep to dataset1 (_mitemp1.dta).
-> Applying keep to dataset2 (_mitemp2.dta).
-> Applying keep to dataset3 (_mitemp3.dta).
-> Applying keep to dataset4 (_mitemp4.dta).
-> Applying keep to dataset5 (_mitemp5.dta).
. mido reshape wide drkany cisgp, i(id) j(wave)
-> Applying reshape to dataset1 (_mitemp1.dta).
(note: j = 1 2 3 4 5 6)
```

<table>
<thead>
<tr>
<th>Data</th>
<th>long</th>
<th>wide</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of obs.</td>
<td>1170</td>
<td>195</td>
</tr>
<tr>
<td>Number of variables</td>
<td>5</td>
<td>14</td>
</tr>
<tr>
<td>j variable (6 values)</td>
<td>wave</td>
<td>(dropped)</td>
</tr>
<tr>
<td>xij variables:</td>
<td>drkany</td>
<td>drkany1 drkany2 ... drkany6</td>
</tr>
<tr>
<td></td>
<td>cisgp</td>
<td>cisgp1 cisgp2 ... cisgp6</td>
</tr>
</tbody>
</table>

```
-> Applying reshape to dataset2 (_mitemp2.dta).
(note: j = 1 2 3 4 5 6)
```

<table>
<thead>
<tr>
<th>Data</th>
<th>long</th>
<th>wide</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of obs.</td>
<td>1170</td>
<td>195</td>
</tr>
<tr>
<td>Number of variables</td>
<td>5</td>
<td>14</td>
</tr>
<tr>
<td>j variable (6 values)</td>
<td>wave</td>
<td>(dropped)</td>
</tr>
<tr>
<td>xij variables:</td>
<td>drkany</td>
<td>drkany1 drkany2 ... drkany6</td>
</tr>
<tr>
<td></td>
<td>cisgp</td>
<td>cisgp1 cisgp2 ... cisgp6</td>
</tr>
</tbody>
</table>

```
-> Applying reshape to dataset3 (_mitemp3.dta).
(note: j = 1 2 3 4 5 6)
```

<table>
<thead>
<tr>
<th>Data</th>
<th>long</th>
<th>wide</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of obs.</td>
<td>1170</td>
<td>195</td>
</tr>
<tr>
<td>Number of variables</td>
<td>5</td>
<td>14</td>
</tr>
<tr>
<td>j variable (6 values)</td>
<td>wave</td>
<td>(dropped)</td>
</tr>
<tr>
<td>xij variables:</td>
<td>drkany</td>
<td>drkany1 drkany2 ... drkany6</td>
</tr>
<tr>
<td></td>
<td>cisgp</td>
<td>cisgp1 cisgp2 ... cisgp6</td>
</tr>
</tbody>
</table>
Tools for multiple imputed datasets

-> Applying reshape to dataset4 (_mitemp4.dta).

(\textit{note: j = 1 2 3 4 5 6})

\begin{verbatim}
data
\end{verbatim}

\begin{verbatim}
long -> wide
\end{verbatim}

\begin{verbatim}
Number of obs. 1170 -> 195
Number of variables 5 -> 14
j variable (6 values) wave -> (dropped)
xij variables:
drkany -> drkany1 drkany2 ... drkany6
cisgp -> cisgp1 cisgp2 ... cisgp6
\end{verbatim}

-> Applying reshape to dataset5 (_mitemp5.dta).

(\textit{note: j = 1 2 3 4 5 6})

\begin{verbatim}
data
\end{verbatim}

\begin{verbatim}
long -> wide
\end{verbatim}

\begin{verbatim}
Number of obs. 1170 -> 195
Number of variables 5 -> 14
j variable (6 values) wave -> (dropped)
xij variables:
drkany -> drkany1 drkany2 ... drkany6
cisgp -> cisgp1 cisgp2 ... cisgp6
\end{verbatim}

\begin{verbatim}
.mici: drkany2 if drkany1==0, bin
(male & female)
\end{verbatim}

Overall estimates -- Binomial --

\begin{verbatim}
| Variable | Obs(min) | Obs(max) | Mean | Std. Err. | [95% Conf. Interval] |
\end{verbatim}

\begin{verbatim}
drkany2 | 136 137 | 0.3034993 | 0.0401668 | 0.2247364 0.3822623*
\end{verbatim}

This provides an estimate of the (cumulative) incidence of alcohol use between waves 1 and 2. The asterisk at the end of the output line is a hyperlink to a warning message indicating that the complete data analyses are not based on the same number of observations (because the if condition defines a slightly different subset in each imputation). Logistic regression may be used (below) to examine association between incidence and covariates of interest.

\begin{verbatim}
.mifit: xi: logistic drkany2 i.cisgp1 if drkany1==0
\end{verbatim}

Overall estimates

\begin{verbatim}
| Variable | Odds Ratio | Std. Err. | t | P>|t| | [95% Conf. Interval] | MI.df |
\end{verbatim}

\begin{verbatim}
_1cisgp1_2 | 0.8641 | 0.40652 | -0.31 | 0.756 | 0.34345 2.174 | 1968.65* |
_1cisgp1_3 | 1.0686 | 0.48456 | 0.15 | 0.884 | 0.43906 2.6007 | 1603.00* |
\end{verbatim}

Finally, you might choose to do a little cleaning up before ending the session.

\begin{verbatim}
for num 1/5: erase tempX.dta
\end{verbatim}

-> erase temp1.dta

-> erase temp2.dta

-> erase temp3.dta
7  Saved Results

mici saves results in $r()$:

Macros
- $r(minp)$: number of multiple imputed datasets
- $r(level)$: confidence level

Matrices
- $r(overall)$: multiple-imputation results and related quantities of interest

mifit saves results in $e()$:

Scalars
- $e(dr_r)$: maximum multiple-imputation degrees of freedom for estimates of regression coefficients
- $e(df_m)$: model degrees of freedom
- $e(obs_{mi})$: number of observations in the $i$th imputed dataset

Macros
- $e(cmd)$: original estimation command issued in the call of mifit
- $e(dep_v)$: name of the dependent variable
- $e(mi_level)$: confidence level

Matrices
- $e(MI_b)$: regression coefficient vector
- $e(MI_V)$: diagonal elements, which are estimates of multiple-imputation variance for the coefficients. Note that it is not a genuine variance–covariance matrix
- $e(MI_df)$: vector of multiple-imputation degrees of freedom, see expression (2) in section 2
- $e(b_{i})$: coefficient vector for the $i$th imputed dataset
- $e(V_{i})$: variance–covariance matrix for the $i$th imputed dataset

8  References


Tools for multiple imputed datasets


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