Multiple-imputation analysis using Stata's `mi` command

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Outline

What is multiple imputation?

- Multiple imputation (MI) is a simulation-based approach for analyzing incomplete data.
- MI replaces missing values with multiple sets of simulated values to complete the data, applies standard analyses to each completed dataset, and adjusts the obtained parameter estimates for missing-data uncertainty (Rubin 1987, 76).
- The objective of MI is not to predict missing values as close as possible to the true ones but to handle missing data in a way resulting in valid statistical inference (Rubin 1996).

Why use multiple imputation?

- It can be more efficient than commonly-used listwise deletion (complete-cases analysis) and can correct for potential bias.
- It is more flexible than fully-parametric methods, e.g. maximum likelihood, purely Bayesian analysis.
- It accounts for missing-data uncertainty and, thus, does not underestimate the variance of estimates like single imputation methods.

Statistical validity of MI

MI yields statistically valid inference if

- an imputation method used is proper per Rubin (1987, 118–119).

  Rubin recommends drawing imputations from a Bayesian posterior predictive distribution of missing data to ensure that imputations are proper.
- the primary, completed-data analysis is statistically valid in the absence of missing data; see Rubin (1987, 116–118) for details.

Notation and some terminology

- *Original data* are the data containing missing values.
- With a slight abuse of terminology, by an *imputation* we mean a copy of the original data in which missing values are imputed.
- M is the number of imputations.
- $m\,(= 0, \ldots, M)$ refers to the original or imputed data: $m = 0$ means original data and $m > 0$ means imputed data. $m = 1$ means the first imputation, $m = 2$ means the second imputation, etc.
- `mi` data are data which have been set up for use by the `mi` command.

Main features

Stata 11's `mi` command provides full support for all three steps of multiple imputation:

- `mi impute` performs imputation (step 1);
- `mi estimate` performs individual completed-data analyses (step 2), and then uses Rubin's combination rules to consolidate the obtained individual estimates into a single set of MI estimates (step 3).

`mi` also offers full data management of multiply-imputed data:

- you can create or drop variables, observations as if you were working with one dataset — `mi` will replicate the changes correctly across the imputed datasets.

Other unique features of `mi`:

- the ability to store multiply-imputed data in different formats — `mi` data styles;
- the ability to verify consistency of the data across multiple copies.

Example: heart attacks

- Consider fictional data recording heart attacks.
- The objective is to examine a relationship between smoking and heart attacks adjusting for age, body mass index, gender, and educational status.

```
. webuse mheart0
(Fictional heart attack data; bmi missing)

. describe

Contains data from http://www.stata-press.com/data/r11/mheart0.dta
  obs:           154                          Fictional heart attack data; bmi
                                                missing
 vars:             9                          19 Jun 2009 10:50
 size:         3,542 (99.9% of memory free)
--------------------------------------------------------------------------------
              storage  display     value
variable name   type   format      label      variable label
--------------------------------------------------------------------------------
attack          byte   %9.0g                  Outcome (heart attack)
smokes          byte   %9.0g                  Current smoker
age             float  %9.0g                  Age, in years
bmi             float  %9.0g                  Body Mass Index, kg/m^2
female          byte   %9.0g                  Gender
hsgrad          byte   %9.0g                  High school graduate
```

(*output omitted*)

- We use simple logistic regression to study the relationship between smoking and heart attacks adjusted for other factors.

```
. logit attack smokes age bmi female hsgrad
Iteration 0:   log likelihood = -91.359017
Iteration 1:   log likelihood = -79.374749
Iteration 2:   log likelihood = -79.342218
Iteration 3:   log likelihood =  -79.34221
Logistic regression                               Number of obs   =        132
                                                  LR chi2(5)      =      24.03
                                                  Prob > chi2     =     0.0002
Log likelihood =  -79.34221                       Pseudo R2       =     0.1315
```

attack	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
smokes	1.544053	.3998329	3.86	0.000	.7603945	2.327711
age	.026112	.017042	1.53	0.125	-.0072898	.0595137
bmi	.1129938	.0500061	2.26	0.024	.0149837	.211004
female	.2255301	.4527558	0.50	0.618	-.6618549	1.112915
hsgrad	.4048251	.4446019	0.91	0.363	-.4665786	1.276229
_cons	-5.408398	1.810603	-2.99	0.003	-8.957115	-1.85968

- To preserve available complete data, we now use multiple imputation to analyze the heart-attack data.
- We examine data for missing values using `misstable summarize`.

```
. misstable summarize
                                                            Obs<.
                                                +------------------------------
                                                | Unique
    Variable |     Obs=.     Obs>.     Obs<.    | values        Min         Max
-------------+--------------------------------+------------------------------
         bmi |        22                 132    |    132   17.22643    38.24214
-----------------------------------------------------------------------------
```

- Let's impute missing values of `bmi`.

First, we declare our data to be `mi` data.

1. We begin by setting a style — we choose a memory-efficient style, `mlong`.

```
. mi set mlong
```

2. We register `bmi`, the variable to be imputed, as an imputation variable (required by `mi impute`).

```
. mi register imputed bmi
(22 m=0 obs. now marked as incomplete)
```

3. We can also register other variables as `regular`. This step is highly recommended but we will skip it for now.

- Because bmi is a continuous measure, we impute it using the regression method.
- We arbitrarily create 5 imputations.
- We set the random-number seed for reproducibility.

```
. mi impute regress bmi attack smokes age female hsgrad, add(5) rseed(123)
Univariate imputation                    Imputations =        5
Linear regression                              added =        5
Imputed: m=1 through m=5                     updated =        0

             |           Observations per m
             |----------------------------------------------
    Variable |   complete   incomplete   imputed |     total
-------------+-----------------------------------+----------
         bmi |        132           22        22 |       154
------------------------------------------------------------
(complete + incomplete = total; imputed is the minimum across m
 of the number of filled in observations.)
```

- We perform logistic analysis of the multiply-imputed data using `mi estimate: logit`.

```
. mi estimate: logit attack smokes age bmi female hsgrad
Multiple-imputation estimates                     Imputations     =          5
Logistic regression                               Number of obs   =        154
                                                  Average RVI     =     0.0564
DF adjustment:   Large sample                     DF:     min     =      78.77
                                                          avg     =   14754.79
                                                          max     =   39201.13
Model F test:       Equal FMI                     F(   5, 3527.0) =       3.39
Within VCE type:          OIM                     Prob > F        =     0.0047

------------------------------------------------------------------------------
      attack |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      smokes |   1.193653   .3579481     3.33   0.001      .492038    1.895268
         age |   .0360079   .0155205     2.32   0.020     .0055845    .0664314
         bmi |   .0985092   .0516418     1.91   0.060     -.004286    .2013044
      female |   -.113328   .4165623    -0.27   0.786    -.9298195    .7031636
      hsgrad |   .1555202   .4034539     0.39   0.700    -.6352593    .9462997
       _cons |  -5.329907   1.800598    -2.96   0.004    -8.893172   -1.766643
------------------------------------------------------------------------------
```

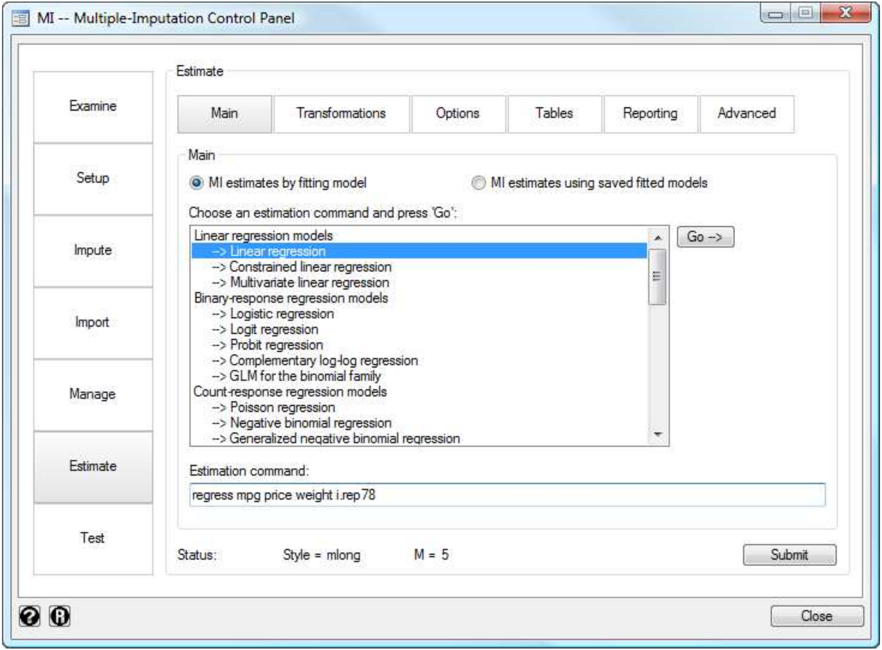
GUI — MI control panel

The MI control panel, which can be invoked from the **Statistics** > **Multiple imputation** menu or by typing

```
. db mi
```

guides you through all the phases of MI.

(NEXT SLIDE)


MI -- Multiple-Imputation Control Panel
Examine
Setup
Impute
Import
Manage
Estimate
Test
Estimate
Main
Transformations
Options
Tables
Reporting
Advanced
Main
MI estimates by fitting model
MI estimates using saved fitted models
Choose an estimation command and press 'Go':
Linear regression models
--> Linear regression
--> Constrained linear regression
--> Multivariate linear regression
Binary-response regression models
--> Logistic regression
--> Logit regression
--> Probit regression
--> Complementary log-log regression
--> GLM for the binomial family
Count-response regression models
--> Poisson regression
--> Negative binomial regression
--> Generalized negative binomial regression
Go -->
Estimation command:
regress mpg price weight i.rep78
Status:
Style = mlong
M = 5
Submit
Close

Declaring data as `mi`

- To use the `mi` command, your data must be declared as `mi` data.
- To set up `mi` data, you need to select an `mi` storage style, the format in which MI data will be stored, and register variables.
- If you are going to impute data, use `mi set` to declare a storage style. If you already have imputed data, use `mi import` to import it to `mi`.
- Use `mi register` to register variables.

`mi` data styles

`mi` supports 4 styles (formats) for storing MI data:

- `flongsep` — full long and separate — imputed data are in separate files, one per imputation;
- `flong` — full long — original and imputed data are in one file, imputations are saved as extra observations;
- `mlong` — marginal long — original and imputed data are in one file, only observations containing imputed values are saved as extra observations. `mlong` is a memory-efficient version of `flong`;
- `wide` — wide — original and imputed data are in one file, imputations are saved as extra variables.

Some tasks are easier in one style than another. You can switch from one style to another during your `mi` session by using `mi convert`.

The role of registered variables in `mi`

`mi` uses a variable's status to verify its consistency across imputations. Registering variables is, in general, not required but highly recommended.

`mi` distinguishes 3 types of variables:

- imputation (`imputed`) — variables containing missing values to be filled in. Such values must be recorded as system missing values. Imputation variables determine the status of observations: complete or incomplete;
- passive (`passive`) — variables which are functions of imputation and/or other passive variables;
- regular (`regular`) — variables which are the same across imputations;
- other variables are treated as unregistered.

`mi` data verification

- Once data are declared as `mi`, the consistency of the `mi` data is checked automatically each time an `mi` subcommand is run. If errors are detected, `mi` reports them and automatically fixes them.
- You can also perform verification at any time by using the `mi update` command.

`mi` verifies that

- complete/incomplete observations are correctly identified by the imputation variables
- regular variables contain the same values in imputed data as in the original data
- imputation variables contain the same nonmissing values in imputed data as in the original data
- passive variables contain the same values in complete observations in imputed data as in the original data
- and more; see **[MI] mi update** for more detail

Importing existing imputations to `mi`

In the heart-attack example we created imputations using `mi impute`. What if you need to analyze multiply-imputed data created outside of Stata?

1. Read file(s) containing multiply-imputed data into Stata; see, for example, **[D] infile**.
2. Use `mi import` to set up the multiply-imputed data in `mi`.

`mi import` supports various styles in which multiply-imputed data can be recorded. For example, `mi import ice` imports MI data recorded in the format used by the user-written command `ice` (Royston 2007), performing imputation via chained equations.

Imputation methods

- Univariate imputation:
  - linear regression for continuous variables
    `mi impute regress`
  - predictive mean matching for continuous variables
    `mi impute pmm`
  - logistic regression for binary variables
    `mi impute logit`
  - ordinal logistic regression for ordinal variables
    `mi impute ologit`
  - multinomial logistic regression for nominal variables
    `mi impute mlogit`
- Multivariate imputation:
  - monotone method for multiple variables of different types
    `mi impute monotone`
  - multivariate normal regression for multiple continuous variables
    `mi impute mvn`

Imputation methods — assumptions

- `mi impute` assumes that missing data are missing at random; that is, missing values do not carry any extra information about why they are missing than what is already available in the observed data.
- `mi impute` creates imputations by simulating from a (approximate) Bayesian posterior predictive distribution of the missing data.
- To further ensure that imputations are proper you must choose an appropriate imputation method and an appropriate imputation model.

`mi impute`'s general syntax

`mi impute` *method model_spec* [, *common_options method_options*]

The two main common options are `add()` and `replace`. These options allow you to perform the following actions:

1. Create imputations or add new imputations to the existing ones:
   `mi impute ..., add(#) ...`
2. Replace existing imputations with new ones:
   `mi impute ..., replace ...`
3. Replace existing imputations and add new ones:
   `mi impute ..., add(#) replace ...`

See **[MI] mi impute** for more details.

Multivariate imputation

In the earlier example we imputed a single variable. More often, multiple variables are needed to be imputed simultaneously.

`mi` offers two commands to perform multivariate imputation:

- `mi impute monotone` implements a noniterative method for imputing multiple variables possibly of different types when the missingness pattern is monotone (Rubin 1987, 170-186).
- `mi impute mvn` implements an iterative MCMC method (data augmentation) for imputing multiple continuous variables under the multivariate normal model (Schafer 1997). The missingness pattern can be arbitrary.

Example: multivariate imputation of heart-attack data

- Consider a version of our heart-attack data in which the `bmi` and `age` variables contain missing values.
- The data are already `mi set`.

```
. webuse mheart5s0
(Fictional heart attack data; bmi and age missing)
. mi describe
  Style:  mlong
          last mi update 19jun2009 10:50:18, 155 days ago
  Obs.:   complete          126
          incomplete         28  (M = 0 imputations)
          ---------------------
          total             154
  Vars.:  imputed:  2; bmi(28) age(12)
          passive: 0
          regular: 4; attack smokes female hsgrad
          system:  3; _mi_m _mi_id _mi_miss
         (there are no unregistered variables)
```

According to `mi describe`:

- Data are set in the `mlong` style.
- Two variables, `bmi` and `age`, contain missing values and are registered as imputed.
- Other variables are registered as regular.
- Data contain no imputations.
- There are 3 system variables, associated with the `mlong` style.
- System variable `_mi_miss` records the status of observations (1 means incomplete) based on imputation variables `age` and `bmi`.
- `_mi_m` records imputation numbers and `_mi_id` records observation identifiers; see **[MI] technical** for details.

- Let's check missingness patterns of the data.
- Because data are already `mi set`, we use `mi misstable` rather than `misstable`.
- We can use `mi misstable patterns` to describe missingness patterns.

```
. mi misstable patterns
   Missing-value patterns
     (1 means complete)

              |   Pattern
    Percent   |  1  2
  ------------+-------------
       82%    |  1  1
              |
       10     |  1  0
        8     |  0  0
  ------------+-------------
      100%    |
  Variables are  (1) age  (2) bmi
```

- We can also use `mi misstable nested` to check if variables are nested with respect to missing values.

```
. mi misstable nested
    1.  age(12) -> bmi(28)
```

- According to `mi misstable`, missing values of age and `bmi` form a monotone missing-value pattern: age is missing only in observations where `bmi` is missing. `bmi` does not have any observations with nonmissing values for which age is missing.
- Thus, we can use `mi impute monotone` to impute `bmi` and age.

```
. mi impute monotone (regress) bmi age = attack smokes hsgrad female, add(5)
Conditional models:
           age: regress age attack smokes hsgrad female
           bmi: regress bmi age attack smokes hsgrad female

Multivariate imputation                    Imputations =        5
Monotone method                                  added =        5
Imputed: m=1 through m=5                       updated =        0

           age: linear regression
           bmi: linear regression

               |              Observations per m
               |----------------------------------------------
      Variable |   complete   incomplete   imputed |     total
---------------+-----------------------------------+----------
           age |        142           12        12 |       154
           bmi |        126           28        28 |       154
--------------------------------------------------------------
(complete + incomplete = total; imputed is the minimum across m
 of the number of filled in observations.)
```

- We used the same univariate imputation method, `regress`, for both `age` and `bmi`.
- We used other complete variables as explanatory variables in the imputation models.
- We created 5 imputations.
- Note that `mi impute monotone` automatically builds the appropriate conditional models.
- Note that `mi impute monotone` automatically orders imputation variables from the most observed to the least observed (`age bmi`) regardless of the order in which they are listed in the specification (`bmi age`).

- Suppose we want to use different sets of predictors when imputing `bmi` and `age`.
- `mi impute mvn` allows specification of custom prediction equations when the `custom` option is used.

```
. mi impute monotone (regress age attack smokes female)              ///
>                    (regress bmi age attack smokes hsgrad female), ///
>                                                                    replace custom

Multivariate imputation                     Imputations =        5
Monotone method                                   added =        0
Imputed: m=1 through m=5                        updated =        5

           age: linear regression
           bmi: linear regression

              |             Observations per m
              |----------------------------------------------
     Variable |   complete   incomplete   imputed |     total
--------------+-----------------------------------+----------
          age |        142           12        12 |       154
          bmi |        126           28        28 |       154
--------------+-----------------------------------+----------

(complete + incomplete = total; imputed is the minimum across m
 of the number of filled in observations.)
```

- We can also use `mi impute mvn` to impute `bmi` and `age`.

```
. mi impute mvn age bmi = attack smokes hsgrad female, replace
Performing EM optimization:
note: 12 observations omitted from EM estimation because of all imputation
      variables missing
  observed log likelihood = -651.75868 at iteration 7

Performing MCMC data augmentation ...

Multivariate imputation                    Imputations =          5
Multivariate normal regression                   added =          0
Imputed: m=1 through m=5                       updated =          5

Prior: uniform                              Iterations =        500
                                               burn-in =        100
                                               between =        100

               |              Observations per m
               |----------------------------------------------
      Variable |   complete   incomplete   imputed |     total
---------------+-----------------------------------+----------
           age |        142           12        12 |       154
           bmi |        126           28        28 |       154
--------------------------------------------------------------
(complete + incomplete = total; imputed is the minimum across m
 of the number of filled in observations.)
```

- When a missing-value pattern is monotone, using `mi impute monotone` is faster because it does not require iteration.

- `mi impute mvn` uses data augmentation, an iterative MCMC method, to impute missing values under a multivariate normal model.
- `mi impute mvn` uses estimates from the EM algorithm as starting values for the MCMC procedure. You can supply your own initial values, if needed, using option `initmcmc()`.
- The default prior is uniform under which posterior mode estimates and maximum-likelihood estimates are equivalent. You can change the default prior specification using option `prior()`.
- The first imputation is drawn after an initial default burn-in period of 100 iterations. You can use option `burnin()` to choose a different burn-in period.
- The subsequent imputations are drawn every 100 (the default) iterations apart. You can change the number of iterations between imputations using option `burnbetween()`.

Estimation using multiple imputation

- `mi estimate` performs analysis of multiply-imputed data.
- `mi estimate` requires `mi` data with at least 2 imputations.
- Basic syntax:

  `mi estimate` [, *options*] : *estimation_command*

- `mi estimate` runs *estimation_command* on all imputed data and reports the MI estimates of coefficients and their standard errors.
- *estimation_command* is one of the supported estimation commands as listed in **[MI] estimation**.

Example

- Recall our first example analyzing heart-attack data containing missing values for `bmi`.

```
. mi estimate: logit attack smokes age bmi female hsgrad
Multiple-imputation estimates                   Imputations       =          5
Logistic regression                             Number of obs     =        154
                                                Average RVI       =     0.0564
DF adjustment:   Large sample                   DF:      min      =      78.77
                                                         avg      =   14754.79
                                                         max      =   39201.13
Model F test:       Equal FMI                   F(   5, 3527.0)  =       3.39
Within VCE type:          OIM                   Prob > F          =     0.0047

------------------------------------------------------------------------------
      attack |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      smokes |   1.193653   .3579481     3.33   0.001      .492038    1.895268
         age |   .0360079   .0155205     2.32   0.020     .0055845    .0664314
         bmi |   .0985092   .0516418     1.91   0.060     -.004286    .2013044
      female |   -.113328   .4165623    -0.27   0.786    -.9298195    .7031636
      hsgrad |   .1555202   .4034539     0.39   0.700    -.6352593    .9462997
       _cons |  -5.329907   1.800598    -2.96   0.004    -8.893172   -1.766643
------------------------------------------------------------------------------
```

- We request more detail about MI estimates by specifying the `vartable` option.
- We also suppress the estimation table by using the `nocitable` option.

```
. mi estimate, vartable nocitable
Multiple-imputation estimates                  Imputations     =          5
Variance information
```

	Imputation variance					Relative
	Within	Between	Total	RVI	FMI	efficiency
smokes	.126167	.001633	.128127	.015535	.015412	.996927
age	.000236	4.1e-06	.000241	.020689	.020471	.995923
bmi	.002066	.000501	.002667	.290903	.244296	.953417
female	.1712	.001937	.173524	.013577	.013484	.997311
hsgrad	.161131	.00137	.162775	.010204	.010152	.997974
_cons	2.66504	.480929	3.24215	.21655	.190724	.963257

Estimating transformations

- Suppose we want to estimate the ratio of coefficients for `bmi` and `age`.

```
. mi estimate (ratio: _b[bmi]/_b[age]), nocoef:   ///
>                logit attack smokes age bmi female hsgrad
Multiple-imputation estimates                  Imputations     =          5
Logistic regression                            Number of obs   =        154
                                               Average RVI     =     0.1149
DF adjustment:   Large sample                  DF:      min    =     376.39
                                                        avg    =     376.39
Within VCE type:          OIM                           max    =     376.39
      command: logit attack smokes age bmi female hsgrad
        ratio: _b[bmi]/_b[age]
```

attack	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ratio	2.720908	1.679848	1.62	0.106	-.5821547	6.02397

- To avoid refitting the completed-data models, we can first save individual estimates to an estimation file (e.g., `myest.ster`):

```
. mi estimate, saving(myest): logit attack smokes age bmi female hsgrad
```

and then use `mi estimate using` to obtain transformations:

```
. mi estimate (ratio: _b[age]/_b[bmi]) using myest
```

Testing hypotheses

After `mi estimate`, you can use

- `mi test` to test the subset of coefficients equal to zero;
- `mi testtransform` to test other linear or nonlinear hypotheses.

`mi test` and `mi testtransform` provide

- the conditional (equal fraction-missing-information, FMI) test of Li et al. (1991);
- the unconditional test of Rubin (1987, 77–78). This test may be preferable when the number of imputations is large and the equal FMI assumption is suspect.
- small-sample adjustments for the tests as described in Marchenko and Reiter (2009).

Testing hypotheses

- For example, to test if coefficients for `smokes`, age, and `bmi` are jointly equal to zero, we type:

```
. mi test smokes age bmi
note: assuming equal fractions of missing information
 ( 1)  [attack]smokes = 0
 ( 2)  [attack]age = 0
 ( 3)  [attack]bmi = 0
       F(  3, 674.9) =    5.46
            Prob > F =    0.0010
```

Analyzing complex multiply-imputed data

- You can use `mi estimate` to analyze complex data such as survey, survival, panel.
- In Stata, prior to analyzing complex data, it must be declared: survey data using `svyset`, survival data using `stset`, panel data using `xtset`.
- To declare complex `mi` data, use the corresponding set command with the `mi` prefix: `mi svyset` for survey `mi` data, `mi stset` for survival `mi` data, `mi xtset` for panel `mi` data
- For example, to declare `mi` survey data, use

```
. mi svyset ...
```

  Then, to fit a model on `mi` survey data, use

```
. mi estimate: svy: ...
```

Using `mi estimate` with user-written commands

- `mi estimate` supports only official commands listed in **[MI] estimation**.
- `mi estimate` can be used with user-written commands if the `cmdok` option is used:

  . mi estimate, cmdok : *user_command*

- When you use `cmdok`, you should verify that
  1. Rubin's combination rules are applicable to the results saved by *user_command*;
  2. *user_command* satisfies technical requirements as listed in "Writing programs for use with `mi`" in **[P] program properties**.

Things to keep in mind about `mi estimate`

When using `mi estimate` always remember that

- `mi estimate` is its own estimation command:
  `mi estimate:` *estimation_command* is not *estimation_command*.

  For example, you use `mi estimate`, not `logit` to replay results after `mi estimate: logit`.

- `mi estimate` always reports results in the coefficient metric under which combination rules are applied regardless of the default reporting metric of *estimation_command*.

  For example, although the `logistic` command reports odds ratios,

  ```
  . mi estimate: logistic ...
  ```

  reports coefficients. You can use `mi estimate`'s `or` option to report odds ratios:

  ```
  . mi estimate, or: ...
  ```

Things to keep in mind about `mi estimate`

- `mi estimate` has its own reporting options; it does not respect reporting options specified with *estimation_command*.

  For example, using

  ```
  . mi estimate: logit ..., or
  ```

  would not report odds ratios but

  ```
  . mi estimate, or: logit ...
  ```

  would.

- `mi estimate` has its own postestimation features, such as `mi test`, and does not support *estimation_command*'s postestimation features.

Manipulating `mi` data

Manipulation of `mi` data can be done in one of two ways:

- repeating the same data-management command on each imputed dataset;
- using a data-management routine specialized for multiply-imputed data. For example, specialized routines are needed to append or merge multiply-imputed data.

Stata offers both:

- Use `mi xeq:` *command* to perform *command* on each imputed dataset.
- Use, e.g., `mi append`, `mi merge`, `mi reshape` to append, merge, and reshape `mi` data; see **[MI] intro** (or type `help mi`) for a list of all `mi`-specific data-management commands.

Quick example: managing observations, variables

- `mi` data contain 1 imputation and are saved in the `flongsep` style.

1. Replace a value:

```
. mi xeq: replace age = 20 in 30
m=0 data:
-> replace age = 20 in 30
(1 real change made)
m=1 data:
-> replace age = 20 in 30
(1 real change made)
```

2. Drop a variable:

```
. mi xeq: drop female
m=0 data:
-> drop female
m=1 data:
-> drop female
```

Creating new variables

- If new variables are regular (constant over imputations), you can use `mi xeq: generate` to create them in any `mi` style and you should then register them as `regular`.
- If new variables are *super varying* (vary over imputations in complete observations), you should use `mi xeq: generate` to create them in the `flong` or `flongsep` styles.
- If new variables are functions of imputation or passive variables (and are not super varying), you should use `mi passive: generate` (or `mi passive: egen`) to create them. Using `mi xeq` for this purpose is not always safe.

Managing imputations

You can use

- `mi impute` to create or add new imputations;
- `mi set m` to delete selected imputations;
- `mi add` to add imputations from a separate file;
- `mi set M` to reset the number of imputations (or create empty imputations in which missing data are not filled in).

Other useful commands

- Use `mi query` to get a short summary of the `mi` settings.
- Use `mi describe` to get a more detailed report about `mi` data.
- Use `mi varying` to identify variables that vary over imputations.

  For example, you can use it to identify imputation and passive variables and then register them using `mi register`. This command also helps to detect potential problems.

Things to remember about data manipulation

When performing data manipulation on `mi` data, remember

- to use the `mi` versions of the data-management routines, if they exist;
- to use `mi xeq` with routines for which there is no `mi` prefix;
- to run `mi update` periodically to ensure consistency of the `mi` data.

Summary

- `mi` accommodates all steps of the MI technique:
  - `mi impute` provides univariate and multivariate methods for filling in missing values;
  - `mi estimate` performs completed-data analysis and combines estimates using Rubin's pooling rules.
- `mi` provides full data-management support.
- `mi` provides 4 styles for storing MI data and can import from 5 styles.
- `mi` verifies consistency of your data at every opportunity.
- `mi` offers postestimation features: testing linear or nonlinear hypotheses.
- `mi` provides elaborate GUI support — MI control panel.
- `mi` offers extensive documentation, manual **[MI] Multiple imputation**.

References

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