# Introduction to Proc MI and Proc MIAnalyze for Multiple Imputation of Missing Data in SAS

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Kathy Welch
CSCAR, The University of Michigan
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# Missing Data is a Problem in Many Studies

- Attrition in longitudinal studies
  - Drug doesn’t work/ side effects
  - Drug works too well
- Item non-response in surveys
  - Don’t answer questions on income, but answer other questions
- Partial non-response
  - Participate in interview, but not physical exam

# Missing Data Mechanisms

- MCAR: missing completely at random, missingness (M) has no relationship to data (Y)

  $p(M|Y) = p(M)$, for all Y
- MAR: Missing At Random, missingness only related to observed data values

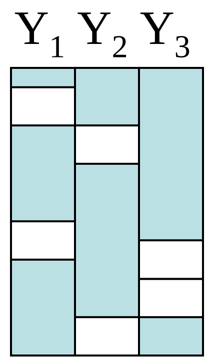
  $p(M|Y)=p(M|Yobs)$, for all Y
- NMAR: Not Missing at random, missingness depends on the ***unobserved*** values of Y
  - AKA, informative missing, non-ignorable missing
- Rubin, 1976, Little and Rubin, 2002

# What to do if NMAR

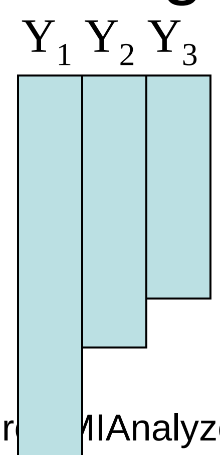
- If data are not missing at random, the missing data *mechanism* needs to be modeled
- There are methods for this, but not implemented in standard software packages

# Missing Data Patterns

- General pattern:




- Monotone pattern:
  - When one value is missing, all subsequent values are missing



# Some methods for handling missing data

- CC: Complete Cases analysis, weighted complete case analysis
- Single Imputation methods
  - Mean imputation
  - Conditional mean imputation
- Multiple Imputation
- Other methods, e.g., bootstrap imputations
- All methods have limitations

# Complete Case Analysis

- Throw away cases with any missing data
- Default method in most SAS procedures (e.g., Proc Reg, Proc GLM)
- Possible problems
  - Can result in serious bias, if missing cases are not MCAR
  - Variances of estimates will be greater than if all cases were used
- May be fine, esp. if amount of missing data is small
- Include in analysis variables that predict missingness (Allison)

# Single Imputation Methods

- Use incomplete data to get a plausible predicted value for the missing data
- Create a “complete” data set for analysis
- Advantage: Once through the data
- But can have problems
  – May be seriously biased
  – May Understate the variability of estimates

# Mean Imputation

- Replace missing data for continuous variables by Mean of non-missing values
- Replace missing data for categorical variables by the mode
- Because marginal distributions are used, associations are distorted
- Standard deviations of completed data are too small (variability is artificially reduced)
- Sample size is overestimated
- Can be less efficient than CC analysis
- Can result in serious bias

# Conditional Mean Imputation

- Conditional on observed values
- Use a regression model to predict the missing values
- Better than unconditional mean, more plausible values
- Standard errors of estimates are still too small
- CC analysis may be better

# Multiple Imputation

- Create m sets of imputations (complete data)
- Analyze the m sets of imputations with usual statistical methods
- Combine estimates to get imputation inference
- Very useful for large public datasets, so users can analyze complete data

# Number of Imputations

- Relative efficiency of a small number (m) of imputations compared to the theoretical infinite number of imputations is high
- 5 imputations the default for Proc MI

Relative Efficiencies*

| | $\lambda$ | | | | |
|---|---|---|---|---|---|
| m | 10% | 20% | 30% | 50% | 70% |
| 3 | 0.9677 | 0.9375 | 0.9091 | 0.8571 | 0.8108 |
| 5 | 0.9804 | 0.9615 | 0.9434 | 0.9091 | 0.8772 |
| 10 | 0.9901 | 0.9804 | 0.9709 | 0.9524 | 0.9346 |
| 20 | 0.9950 | 0.9901 | 0.9852 | 0.9756 | 0.9662 |

*Table 44.5 from SAS documentation for Proc MI, SAS 9.2

# Proper Multiple Imputation Methods

- Each dataset is a random draw from the joint posterior predictive distribution of missing values and parameters of the distribution
- The uncertainty in estimating $\theta$ is taken into account
  – Propagate the error in estimating $\theta$ in the imputations (this is good)
- Estimates have high efficiency
- The accuracy increases with m, and the percent of complete data

# Imputation Model vs. Analysis Model

- Imputation model may use more variables than analysis model
- This is OK
  - Imputation may use many more variables, even though not of substantive interest
  - Different analysts may want to use different predictors in their models
- Improved efficiency and less bias by using more variables for imputation model
- But try to use variables in imputation that are at least helpful for imputation of missing values

# Combining Estimates from Multiple Imputation

$$\overline{\Theta} = \frac{1}{m}\sum_{m=1}^{M}\hat{\Theta}_m$$ Combined Parameter Estimate

$$T = \overline{W} + (1 + \frac{1}{m})B$$ Total variance

$$\overline{W} = \frac{1}{m}\sum_{m=1}^{M}W_m$$ Within-imputation variance

$$B = \frac{1}{m-1}\sum_{m=1}^{M}(\hat{\Theta}_m - \overline{\Theta})^2$$ Between-imputation variance

# Combining Estimates (Cont)

Fraction of Missing Information

$$r = \frac{(1+1/m)B}{\bar{W} + (1+1/m)B}$$

Degrees of Freedom

$$\nu = (m-1)/r^2$$

Degrees of Freedom are increased by having more imputations, or less missing data

# SAS Proc MI Methods for Multiple Imputation

- Methods available in Proc MI depend on missing data pattern
- For arbitrary missing data pattern use Markov-chain Monte Carlo (MCMC) method
  - Based on Bayes methods
  - Proper Imputation
  - Assumes a multivariate normal distribution
  - This may be problematic, esp. for missing categorical variables, but not too bad
- Can be used to get to a monotone missing data pattern, then another method, such as logistic regression for categorical variables, may be used

# Proc MI Methods Available for Different Missing Data Patterns

| Pattern of Missingness | Type of Imputed Variable | Recommended Methods |
|---|---|---|
| Monotone | Continuous | Regression<br>Predicted Mean Matching<br>Propensity Score |
| Monotone | Classification (Ordinal) | Logistic Regression |
| Monotone | Classification (Nominal) | Discriminant Function Method |
| Arbitrary | Continuous | MCMC Full-Data Imputation<br>MCMC Monotone-Data Imputation |

Table 44.3 from Proc MI documentation, SAS 9.1.3

# Example Using Proc MI and MIAnalyze

- LSOA study (Longitudinal Study of Aging, NCHS)

http://www.cdc.gov/nchs/about/otheract/aging/lsoa1.htm

- Baseline data collected in 1984, follow-up in 1986.
- 5151 participants, aged 70 to 99 in 1984
- 64% female
- Want to model changes in ADL (restrictions in Activities of Daily Living) from 1984 to 1986
- Missing data on over 21% for ADL in 1986

# Variables in LSOA Dataset

Variables in Creation Order

| # | Variable | Type | Len | Label |
|---|---|---|---|---|
| 1 | SEX | Num | 3 | 1=MALE 2=FEMALE |
| 2 | AGE84 | Num | 3 | Age during 1984 |
| 3 | RACER | Num | 3 | 1=WHITE 2=BLACK 3=OTHER |
| 4 | EDUC | Num | 3 | Education of individual-completed years |
| 5 | POVERTY | Num | 3 | NHIS poverty index |
| 6 | OWNBUYR | Num | 3 | Own/buying recode |
| 7 | MORTGAGE | Num | 3 | Fully paid for or mortgage being paid |
| 8 | AMTOWED | Num | 4 | Amount principal still owed |
| 9 | PRESVAL | Num | 4 | Present value of place |
| 10 | NUMADL | Num | 3 | Number of ADLs, 1984 |
| 11 | NUMADL2R | Num | 3 | Number of ADLs, 1986 |
| 12 | FNLWGT2 | Num | 3 | Final 1986 LSOA weight |
| 13 | STRATUM | Num | 8 | |
| 14 | PSU | Num | 8 | |

# LSOA Analysis Plan

- Check pattern of missing data
- Create five multiply imputed datasets using Proc MI
- Carry out a regression analysis of the five datasets using Proc Reg
- Combine the estimates from the five datasets to get the MI estimates, using Proc MIAnalyze
- Carry out a CC analysis for comparison

# LSOA Descriptives for Original Dataset

The MEANS Procedure

| Variable | N | N Miss | Mean | Std Dev |
|---|---|---|---|---|
| diffadl | 4048 | 1103 | 0.2197777 | 0.5834531 |
| POVERTY | 4229 | 922 | 1.1941357 | 0.3955806 |
| own | 5015 | 136 | 0.6638086 | 0.4724524 |
| EDUC | 5053 | 98 | 9.7573719 | 3.7452672 |
| AGE84 | 5151 | 0 | 78.2071442 | 6.0010675 |
| SEX | 5151 | 0 | 1.6396816 | 0.4801394 |
| black | 5151 | 0 | 0.1087168 | 0.3113137 |
| other | 5151 | 0 | 0.0108717 | 0.1037091 |

Much missing data on the outcome variable

# Proc MI SAS Code

```
proc mi data=lsoa nimpute=5 out=OUTMI
seed=3355;

var poverty own sex black other educ
age84 logadl logadl2r ;

run;
```

OUTMI contains the five multiply-imputed datasets

_IMPUTATION_ variable indexes imputations

# Proc MI Model Information

```
           The MI Procedure

                       Model Information

Data Set                              WORK.LSOA
Method                                MCMC
Multiple Imputation Chain             Single Chain
Initial Estimates for MCMC            EM Posterior Mode
Start                                 Starting Value
Prior                                 Jeffreys
Number of Imputations                 5
Number of Burn-in Iterations          200
Number of Iterations                  100
Seed for random number generator      3355
```

# Proc MI Missing Data Patterns

Missing Data Patterns

| Group | POVERTY | own | SEX | black | other | EDUC | AGE84 | logadl | logadl2r | Freq |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | X | X | X | X | X | X | X | X | X | 3268 |
| 2 | X | X | X | X | X | X | X | X | . | 791 |
| 3 | X | X | X | X | X | X | X | . | X | 7 |
| 4 | X | X | X | X | X | X | X | . | . | 7 |
| 5 | X | X | X | X | X | . | X | X | X | 28 |
| 6 | X | X | X | X | X | . | X | X | . | 27 |
| 7 | X | X | X | X | X | . | X | . | X | 1 |
| 8 | X | . | X | X | X | X | X | X | X | 77 |
| 9 | X | . | X | X | X | X | X | X | . | 21 |
| 10 | X | . | X | X | X | . | X | X | X | 2 |
| 11 | . | X | X | X | X | X | X | X | X | 624 |

# Proc MI Missing Data Patterns: Group Means

Missing Data Patterns

| | | Group Means | | | |
|---|---|---|---|---|---|
| Group | Percent | POVERTY | own | SEX | black |
| 1 | 63.46 | 1.186047 | 0.686965 | 1.646879 | 0.109241 |
| 2 | 15.36 | 1.231353 | 0.596713 | 1.573957 | 0.113780 |
| 3 | 0.14 | 1.285714 | 0.857143 | 1.571429 | 0 |
| 4 | 0.14 | 1.142857 | 0.571429 | 1.428571 | 0.142857 |
| 5 | 0.54 | 1.178571 | 0.571429 | 1.678571 | 0.178571 |
| 6 | 0.52 | 1.259259 | 0.370370 | 1.666667 | 0.222222 |
| 7 | 0.02 | 1.000000 | 1.000000 | 2.000000 | 0 |
| 8 | 1.50 | 1.155844 | . | 1.532468 | 0.077922 |
| 9 | 0.41 | 1.142857 | . | 1.476190 | 0.095238 |
| 10 | 0.04 | 1.000000 | . | 1.500000 | 0.500000 |
| 11 | 12.12 | . | 0.692308 | 1.684295 | 0.105769 |

# Proc MI Variance Information

Multiple Imputation Variance Information

| Variable | Variance Between | Variance Within | Variance Total | DF |
|---|---|---|---|---|
| POVERTY | 0.000001824 | 0.000030417 | 0.000032606 | 749.29 |
| own | 0.000000864 | 0.000043349 | 0.000044386 | 2981.6 |
| EDUC | 0.000022363 | 0.002728 | 0.002755 | 4547.1 |
| logadl | 0.000000234 | 0.000070284 | 0.000070565 | 5024.8 |
| logadl2r | 0.000024269 | 0.000098270 | 0.000127 | 75.09 |

Multiple Imputation Variance Information

| Variable | Relative Increase in Variance | Fraction Missing Information | Relative Efficiency |
|---|---|---|---|
| POVERTY | 0.071951 | 0.069216 | 0.986346 |
| own | 0.023922 | 0.023630 | 0.995296 |
| EDUC | 0.009836 | 0.009787 | 0.998046 |
| logadl | 0.003991 | 0.003983 | 0.999204 |
| logadl2r | 0.296360 | 0.248006 | 0.952743 |

# Proc MI Parameter Estimates

Multiple Imputation Parameter Estimates

| Variable | Mean | Std Error | 95% Confidence Limits | | DF |
|---|---|---|---|---|---|
| POVERTY | 1.194470 | 0.005710 | 1.183260 | 1.205680 | 749.29 |
| own | 0.664994 | 0.006662 | 0.651931 | 0.678057 | 2981.6 |
| EDUC | 9.743557 | 0.052489 | 9.640652 | 9.846461 | 4547.1 |
| logadl | 0.349539 | 0.008400 | 0.333070 | 0.366007 | 5024.8 |
| logadl2r | 0.559964 | 0.011287 | 0.537480 | 0.582448 | 75.09 |

Multiple Imputation Parameter Estimates

| Variable | Minimum | Maximum | Mu0 | t for H0: Mean=Mu0 | Pr > \|t\| |
|---|---|---|---|---|---|
| POVERTY | 1.193273 | 1.196416 | 0 | 209.18 | <.0001 |
| own | 0.663869 | 0.665959 | 0 | 99.81 | <.0001 |
| EDUC | 9.738145 | 9.749231 | 0 | 185.63 | <.0001 |
| logadl | 0.348811 | 0.350080 | 0 | 41.61 | <.0001 |
| logadl2r | 0.554439 | 0.567925 | 0 | 49.61 | <.0001 |

# Modify Data and Check Means

```
/*Create Difference on Log Scale AFTER Imputation*/
data OUTMI;
  set OUTMI;
  diffadl = logadl2r - logadl;
run;
proc means data=outmi;
by _imputation_;
run;
```

# Descriptives for Imputation 1

```
------------------------------- _Imputation_=1 --------------------------------

                              The MEANS Procedure

                             N
Variable          N       Miss         Minimum         Maximum            Mean
------------------------------------------------------------------------------
SEX            5150          0       1.0000000       2.0000000       1.6398058
AGE84          5150          0      70.0000000      99.0000000      78.2077670
RACER          5150          0       1.0000000       3.0000000       1.1304854
EDUC           5150          0      -0.6051802      18.0000000       9.7473659
POVERTY        5150          0      -0.3943656       2.7625847       1.1964162
own            5150          0      -0.7833835       1.8704920       0.6651582
logadl2r       5150          0      -1.1814288       2.8560990       0.5544391
logadl         5150          0      -0.2376750       2.0794415       0.3498080
black          5150          0               0       1.0000000       0.1087379
other          5150          0               0       1.0000000       0.0108738
ownmiss        5150          0               0       1.0000000       0.0264078
povmiss        5150          0               0       1.0000000       0.1788350
diffadl        5150          0      -2.0794415       2.3073451       0.2046311
------------------------------------------------------------------------------
```

# Descriptives for Imputation 2

------------------------------- _Imputation_=2 -------------------------------

| Variable | N | N Miss | Minimum | Maximum | Mean |
|---|---|---|---|---|---|
| SEX | 5150 | 0 | 1.0000000 | 2.0000000 | 1.6398058 |
| AGE84 | 5150 | 0 | 70.0000000 | 99.0000000 | 78.2077670 |
| RACER | 5150 | 0 | 1.0000000 | 3.0000000 | 1.1304854 |
| EDUC | 5150 | 0 | 0 | 18.0000000 | 9.7492314 |
| POVERTY | 5150 | 0 | -0.0334959 | 2.4663084 | 1.1953344 |
| own | 5150 | 0 | -0.8350119 | 2.0972619 | 0.6657782 |
| logadl2r | 5150 | 0 | -1.6669717 | 3.1120230 | 0.5679253 |
| logadl | 5150 | 0 | -0.6301672 | 2.0794415 | 0.3500805 |
| black | 5150 | 0 | 0 | 1.0000000 | 0.1087379 |
| other | 5150 | 0 | 0 | 1.0000000 | 0.0108738 |
| ownmiss | 5150 | 0 | 0 | 1.0000000 | 0.0264078 |
| povmiss | 5150 | 0 | 0 | 1.0000000 | 0.1788350 |
| diffadl | 5150 | 0 | -2.0794415 | 2.1250189 | 0.2178448 |

# SAS Code for Proc Reg

```
proc reg data=OUTMI outest=OUTREG covout ;
   by _Imputation_;
   model diffadl=poverty own educ logadl age84 sex black other;
run;
```

# Output from Regression for Imputation 1

```
                       The REG Procedure
                         Model: MODEL1
                 Dependent Variable: diffadl

         Number of Observations Read        5150
         Number of Observations Used        5150

                      Parameter Estimates

                       Parameter      Standard
Variable     DF         Estimate         Error    t Value    Pr > |t|

Intercept     1         -1.06429       0.11564      -9.20      <.0001
POVERTY       1          0.00564       0.02052       0.27      0.7836
own           1         -0.04346       0.01666      -2.61      0.0091
EDUC          1         -0.00714       0.00220      -3.25      0.0012
logadl        1         -0.33447       0.01335     -25.06      <.0001
AGE84         1          0.01892       0.00135      14.05      <.0001
SEX           1         -0.00591       0.01627      -0.36      0.7163
black         1          0.08336       0.02585       3.22      0.0013
other         1         -0.13478       0.07383      -1.83      0.0680
```

# Output from Regression for Imputation 2

The REG Procedure
Model: MODEL1
Dependent Variable: diffadl

| | |
|---|---|
| Number of Observations Read | 5150 |
| Number of Observations Used | 5150 |

Parameter Estimates

| Variable | DF | Parameter Estimate | Standard Error | t Value | Pr > \|t\| |
|---|---|---|---|---|---|
| Intercept | 1 | -1.11195 | 0.11696 | -9.51 | <.0001 |
| POVERTY | 1 | 0.04296 | 0.02096 | 2.05 | 0.0405 |
| own | 1 | -0.04476 | 0.01688 | -2.65 | 0.0080 |
| EDUC | 1 | -0.00755 | 0.00223 | -3.39 | 0.0007 |
| logadl | 1 | -0.33505 | 0.01350 | -24.83 | <.0001 |
| AGE84 | 1 | 0.01895 | 0.00136 | 13.89 | <.0001 |
| SEX | 1 | 0.00683 | 0.01648 | 0.41 | 0.6784 |
| black | 1 | 0.07137 | 0.02622 | 2.72 | 0.0065 |
| other | 1 | -0.16516 | 0.07474 | -2.21 | 0.0272 |

# Proc MIAnalyze Code to Combine Estimates Across Imputations

```
proc mianalyze data=OUTREG;
   modeleffects Intercept poverty own educ logadl
age84 sex black other;
run;
```

# Proc MIAnalyze Output

The MIANALYZE Procedure

Model Information

| | |
|---|---|
| Data Set | WORK.OUTREG |
| Number of Imputations | 5 |

Multiple Imputation Variance Information

| Parameter | Variance Between | Variance Within | Variance Total | DF |
|---|---|---|---|---|
| Intercept | 0.001782 | 0.013592 | 0.015730 | 216.5 |
| poverty | 0.000324 | 0.000432 | 0.000821 | 17.816 |
| own | 0.000310 | 0.000282 | 0.000655 | 12.358 |
| educ | 0.000000724 | 0.000004891 | 0.000005760 | 175.62 |
| logadl | 0.000112 | 0.000181 | 0.000315 | 21.953 |
| age84 | 0.000000485 | 0.000001842 | 0.000002424 | 69.323 |
| sex | 0.000073830 | 0.000269 | 0.000357 | 65.112 |
| black | 0.000175 | 0.000680 | 0.000890 | 71.717 |
| other | 0.002603 | 0.005532 | 0.008655 | 30.722 |

# Proc MIAnalyze Output (Cont)

Multiple Imputation Parameter Estimates

| Parameter | Estimate | Std Error | 95% Confidence Limits | | DF |
|---|---|---|---|---|---|
| Intercept | -1.081213 | 0.125421 | -1.32842 | -0.83401 | 216.5 |
| poverty | 0.035685 | 0.028650 | -0.02455 | 0.09592 | 17.816 |
| own | -0.031520 | 0.025584 | -0.08708 | 0.02404 | 12.358 |

Multiple Imputation Parameter Estimates

| Parameter | Minimum | Maximum |
|---|---|---|
| Intercept | -1.132226 | -1.024379 |
| poverty | 0.005635 | 0.053830 |
| own | -0.044841 | -0.010716 |

Multiple Imputation Parameter Estimates

| Parameter | Theta0 | t for H0: Parameter=Theta0 | Pr > \|t\| |
|---|---|---|---|
| Intercept | 0 | -8.62 | <.0001 |
| poverty | 0 | 1.25 | 0.2291 |
| own | 0 | -1.23 | 0.2409 |

# Proc MIAnalyze Output (Cont)

Multiple Imputation Parameter Estimates

| Parameter | Estimate | Std Error | 95% Confidence Limits | | DF |
|---|---|---|---|---|---|
| educ | -0.008150 | 0.002400 | -0.01289 | -0.00341 | 175.62 |
| logadl | -0.341935 | 0.017754 | -0.37876 | -0.30511 | 21.953 |
| age84 | 0.018647 | 0.001557 | 0.01554 | 0.02175 | 69.323 |
| sex | 0.002601 | 0.018906 | -0.03516 | 0.04036 | 65.112 |
| black | 0.070117 | 0.029827 | 0.01065 | 0.12958 | 71.717 |
| other | -0.123315 | 0.093033 | -0.31313 | 0.06650 | 30.722 |

| Parameter | Minimum | Maximum |
|---|---|---|
| educ | -0.009317 | -0.007142 |
| logadl | -0.360206 | -0.334471 |
| age84 | 0.017851 | 0.019504 |
| sex | -0.005912 | 0.014089 |
| black | 0.049046 | 0.083361 |
| other | -0.165156 | -0.034706 |

| Parameter | Theta0 | t for H0: Parameter=Theta0 | Pr > \|t\| |
|---|---|---|---|
| educ | 0 | -3.40 | 0.0008 |
| logadl | 0 | -19.26 | <.0001 |
| age84 | 0 | 11.98 | <.0001 |
| sex | 0 | 0.14 | 0.8910 |
| black | 0 | 2.35 | 0.0215 |
| other | 0 | -1.33 | 0.1948 |

# Impute Values for Poverty (Binary) Using Proc Logistic on Imputed Data

```
data SIX;
  set OUTMI;
  if povmiss=1 then poverty = .;
run;
proc mi data=SIX nimpute=1 out=OUTMI2 seed=3355;
   by _Imputation_;
   class POVERTY;
   monotone logistic (POVERTY = own educ logadl logadl2r age84
sex black other / details);
   var  own educ logadl logadl2r age84 sex black other  poverty;
run;
proc reg data=OUTMI2  outest=OUTREG2 covout ;
  by _imputation_;
  model diffadl=poverty own educ logadl age84 sex black other;
run;
```

# Output from Complete Case Analysis

The REG Procedure
Model: MODEL1
Dependent Variable: diffadl

| | |
|---|---|
| Number of Observations Read | 5151 |
| Number of Observations Used | 3268 |
| Number of Observations with Missing Values | 1883 |

Analysis of Variance

| Source | DF | Sum of Squares | Mean Square | F Value | Pr > F |
|---|---|---|---|---|---|
| Model | 8 | 121.35294 | 15.16912 | 50.43 | <.0001 |
| Error | 3259 | 980.21561 | 0.30077 | | |
| Corrected Total | 3267 | 1101.56855 | | | |

| | | | |
|---|---|---|---|
| Root MSE | 0.54843 | R-Square | 0.1102 |
| Dependent Mean | 0.20687 | Adj R-Sq | 0.1080 |
| Coeff Var | 265.10481 | | |

# Compare CC vs. MI Results

| | CC Analysis | | | | Proc MI | | | |
|---|---|---|---|---|---|---|---|---|
| Variable | Estimate | SE | df | p-value | Estimate | SE | df | p-value |
| Int | -0.84897 | 0.14929 | 3259 | <.0001 | -1.081213 | 0.125421 | 216.5 | <.0001 |
| Poverty | 0.03078 | 0.02626 | 3259 | 0.2412 | 0.035685 | 0.028650 | 17.816 | 0.2291 |
| Own | -0.01959 | 0.02131 | 3259 | 0.3580 | -0.031520 | 0.025584 | 12.358 | 0.2409 |
| Educ | -0.00922 | 0.00278 | 3259 | 0.0009 | -0.008150 | 0.002400 | 175.62 | 0.0008 |
| Logadl | -0.34402 | 0.01836 | 3259 | <.0001 | -0.341935 | 0.017754 | 21.953 | <.0001 |
| Age84 | 0.01631 | 0.00175 | 3259 | <.0001 | 0.018647 | 0.001557 | 69.323 | <.0001 |
| Sex | -0.02703 | 0.02056 | 3259 | 0.1886 | 0.002601 | 0.018906 | 65.112 | 0.8910 |
| Black | 0.03811 | 0.03223 | 3259 | 0.2372 | 0.070117 | 0.029827 | 71.717 | 0.0215 |
| Other | -0.08840 | 0.09632 | 3259 | 0.3588 | -0.123315 | 0.093033 | 30.722 | 0.1948 |

# Summing Up

- There are many methods for analyzing missing data with missing values
- No method is perfect
- CC analysis is better than some mean imputation methods
- Multiple imputation is better than single imputation
- Uncertainty in parameter estimates is correctly maintained in MI methods

# References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