Testing different imputation methods on PUMS (MAR) - Generative Adversarial Imputation Nets (GAIN)

```r
# load dataset: df
load('../../Datasets/ordinalPUMS.Rdata')

# take 10,000 samples: df
set.seed(0)
n = 10000
sample <- sample(nrow(df), size = 10000)
df <- df[sample,]

# create MCAR scneario with 45% chance of missing: df_observed
missing_prob = 0.45
df_observed <- df
missing_col = c(1,3,7,9,10,11)

# Make VEH and WKL MCAR
missing_col_MCAR = c(1,10)
for (col in missing_col_MCAR) {
  missing_ind <- rbernoulli(n,p = missing_prob)
  df_observed[missing_ind, col] <- NA
}

# Make the rest MAR
numeric_df = sapply(df, as.numeric)
normalized_df = t(t(numeric_df-1)/(apply(numeric_df, MARGIN = 2, FUN = max)-1))
missing_col_MAR = c(3,7,9,11)
fully_observed_col = c(2,4,5,6,8)
beta_NP = c(-0.05, -1.5, 0.6, -2, -0.05)+c(0,0.45,0.45,0.45,0)
beta0_NP = -0.05
beta_SCHL = c(-3, 3, -0.75, 0.05, -0.2)+c(0.5,0.5,0.5,0,0)
beta0_SCHL = 0.05
beta_AGEP = c(0.05, -0.2, 0.05, -1.25, 1)+c(0,0,0,1.1,1.1)
beta0_AGEP = -0.05
beta_PINCP = c(3, -0.05, -2.5, 0.05, -1)+c(0.5,0,0.5,0,0.5)
beta0_PINCP = -0.05

# missing probability for NP
prob_NP = apply(t(t(normalized_df[, fully_observed_col])*beta_NP)+beta0_NP, MARGIN = 1, sum)
prob_NP = exp(prob_NP)/(exp(prob_NP)+1)
indicator = rbernoulli(n, p = prob_NP)
df_observed[indicator, missing_col_MAR[1]] <- NA

# missing probability for SCHL
prob_SCHL = apply(t(t(normalized_df[, fully_observed_col])*beta_SCHL)+beta0_SCHL, MARGIN = 1, sum)
prob_SCHL = exp(prob_SCHL)/(exp(prob_SCHL)+1)
indicator = rbernoulli(n, p = prob_SCHL)
df_observed[indicator, missing_col_MAR[2]] <- NA
```

```r
# missing probability for AGEP
prob_AGEP = apply(t(t(normalized_df[, fully_observed_col])*beta_AGEP)+beta0_AGEP, MARGIN = 1, sum)
prob_AGEP = exp(prob_AGEP)/(exp(prob_AGEP)+1)
indicator = rbernoulli(n, p = prob_AGEP)
df_observed[indicator, missing_col_MAR[3]] <- NA

# missing probability for PINCP
prob_PINCP = apply(t(t(normalized_df[, fully_observed_col])*beta_PINCP)+beta0_PINCP, MARGIN = 1, sum)
prob_PINCP = exp(prob_PINCP)/(exp(prob_PINCP)+1)
indicator = rbernoulli(n, p = prob_PINCP)
df_observed[indicator, missing_col_MAR[4]] <- NA

# 44.99% missing
apply(is.na(df_observed), MARGIN = 2, mean)
```

```
##    VEH     MV     NP   RMSP    ENG  MARHT   SCHL RACNUM   AGEP    WKL  PINCP
## 0.4554 0.0000 0.4645 0.0000 0.0000 0.0000 0.4465 0.0000 0.4328 0.4552 0.4454
```

Generative Adversarial Imputation Nets (GAIN)

reference: https://arxiv.org/abs/1806.02920

```r
# Load imputed dataset
d1 = read.csv('../../GAIN/imputed_dataset/MAR_PUMS01_45percent_1.csv', header = FALSE, sep = ',')
d2 = read.csv('../../GAIN/imputed_dataset/MAR_PUMS01_45percent_2.csv', header = FALSE, sep = ',')
d3 = read.csv('../../GAIN/imputed_dataset/MAR_PUMS01_45percent_3.csv', header = FALSE, sep = ',')
d4 = read.csv('../../GAIN/imputed_dataset/MAR_PUMS01_45percent_4.csv', header = FALSE, sep = ',')
d5 = read.csv('../../GAIN/imputed_dataset/MAR_PUMS01_45percent_5.csv', header = FALSE, sep = ',')
colnames(d1) = colnames(df)
colnames(d2) = colnames(df)
colnames(d3) = colnames(df)
colnames(d4) = colnames(df)
colnames(d5) = colnames(df)
imputed_df = rbind(d1, d2, d3, d4, d5)
```

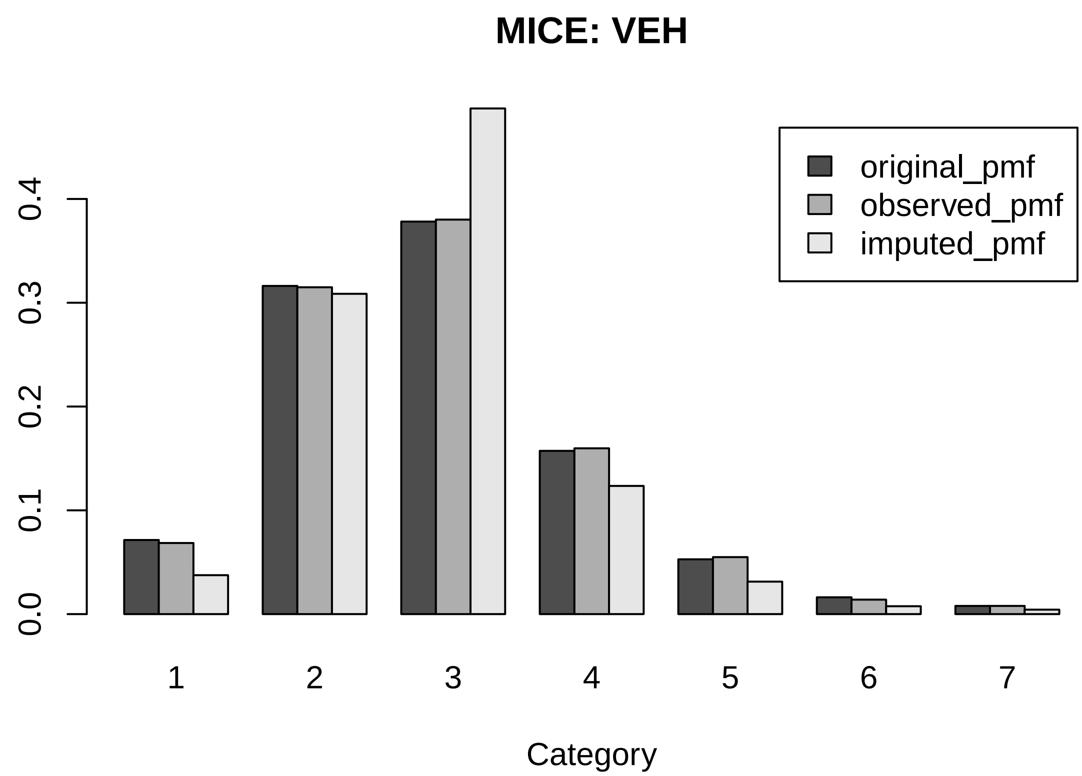
Diagnostics

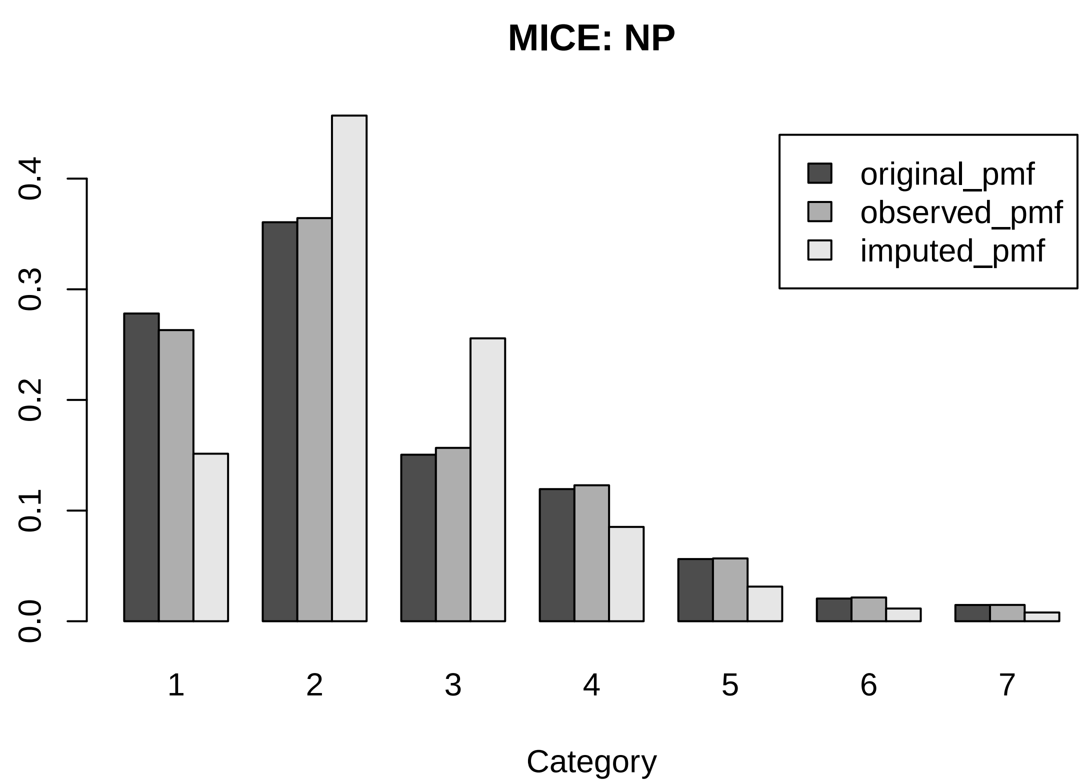
Assess bivariate joint distribution

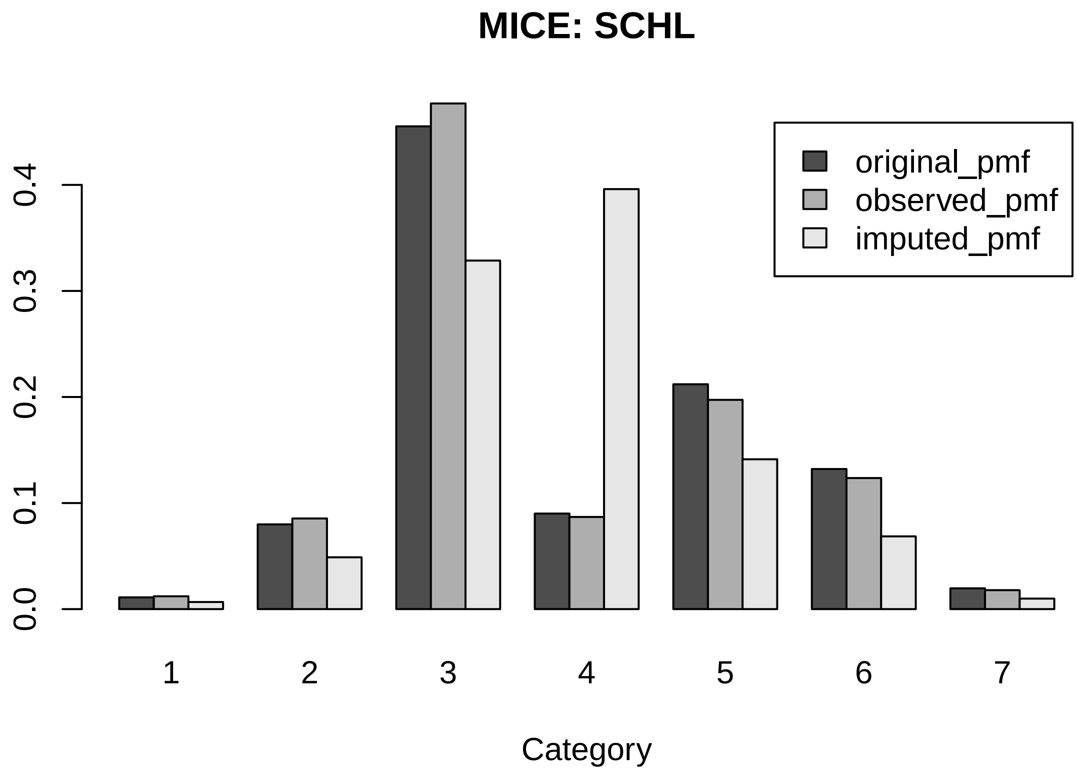
Assess bivariate joint distribution

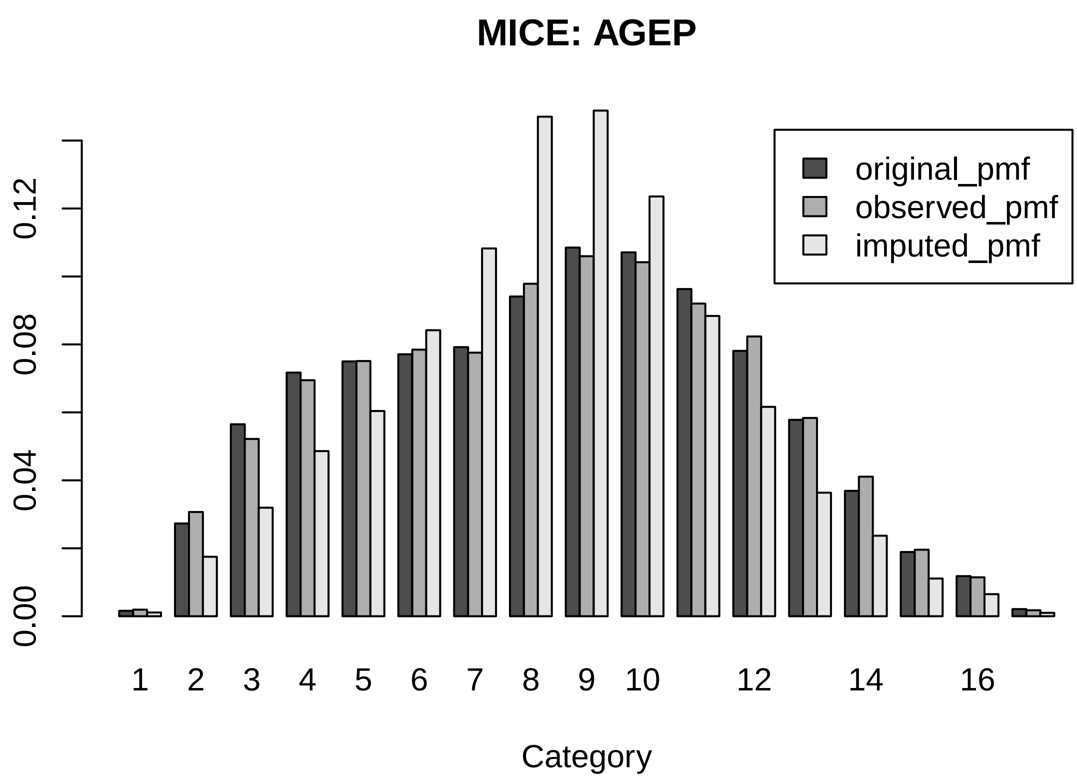
```r
# calculate rmse
numeric_df = sapply(df, as.numeric)
normalized_df = t(t(numeric_df-1)/(apply(numeric_df, MARGIN = 2, FUN = max)-1))
numeric_impute = sapply(d1, as.numeric)
normalized_impute = t(t(numeric_impute-1)/(apply(numeric_df, MARGIN = 2, FUN = max)-1))

missing_matrix = is.na(df_observed)

rmse = sqrt(sum((normalized_df[missing_matrix] - normalized_impute[missing_matrix])^2)/sum(missing_matr
rmse
```

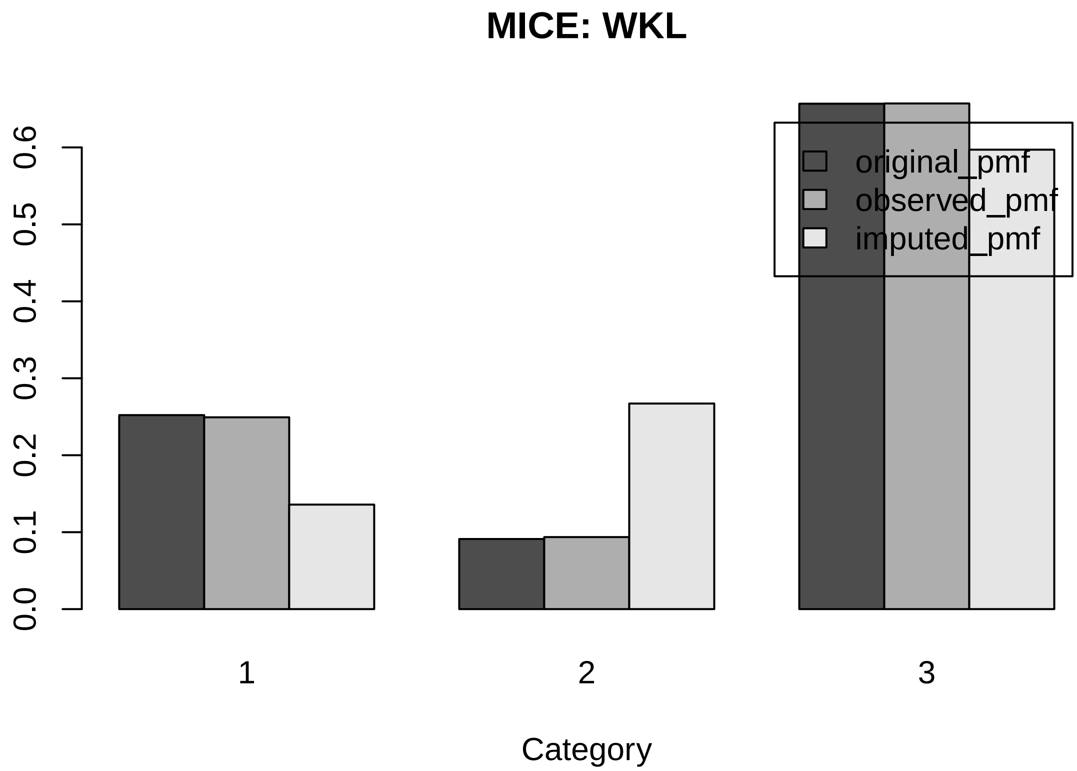
```
## [1] 0.260412
```

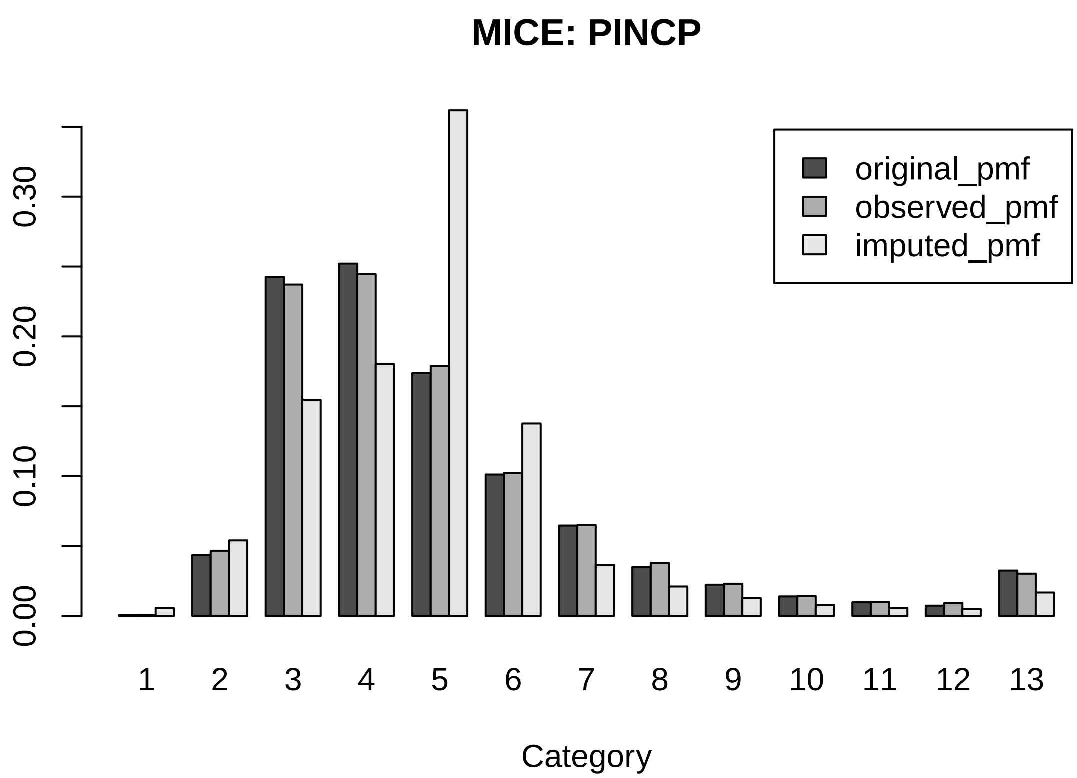

MICE: VEH
original_pmf
observed_pmf
imputed_pmf
0.0
0.1
0.2
0.3
0.4
1
2
3
4
5
6
7
Category

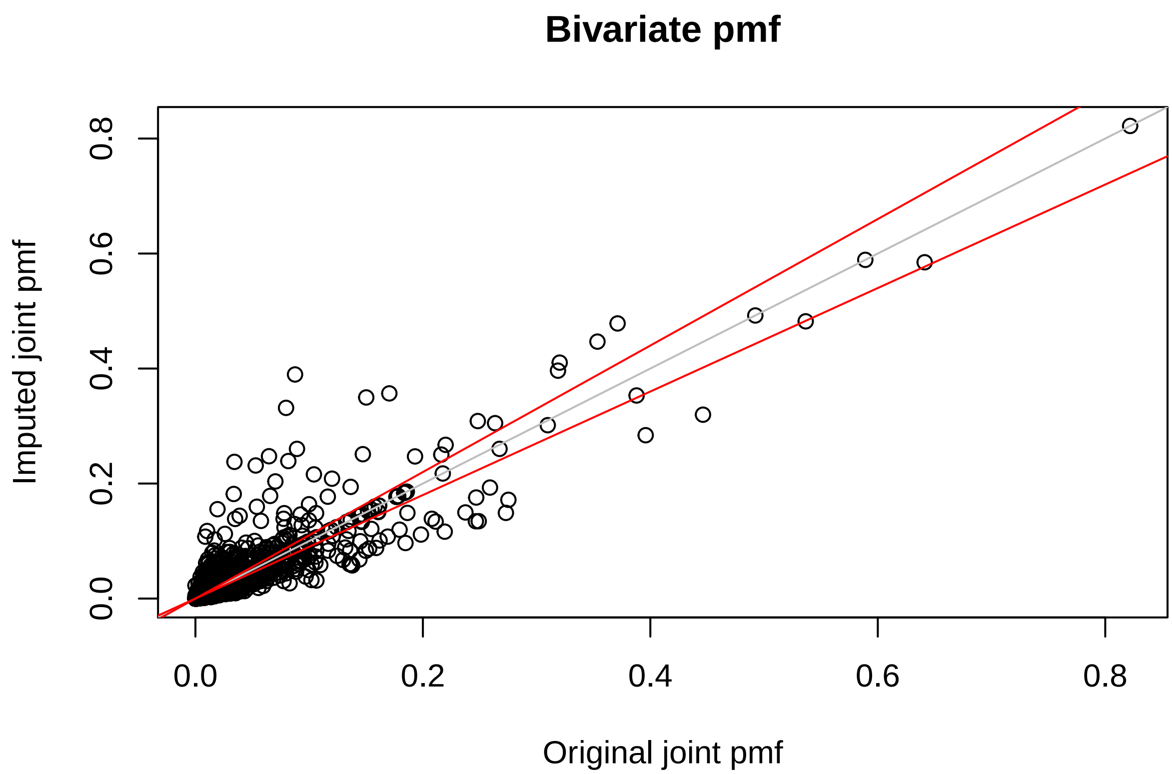

MICE: NP
original_pmf
observed_pmf
imputed_pmf
0.0
0.1
0.2
0.3
0.4
1
2
3
4
5
6
7
Category

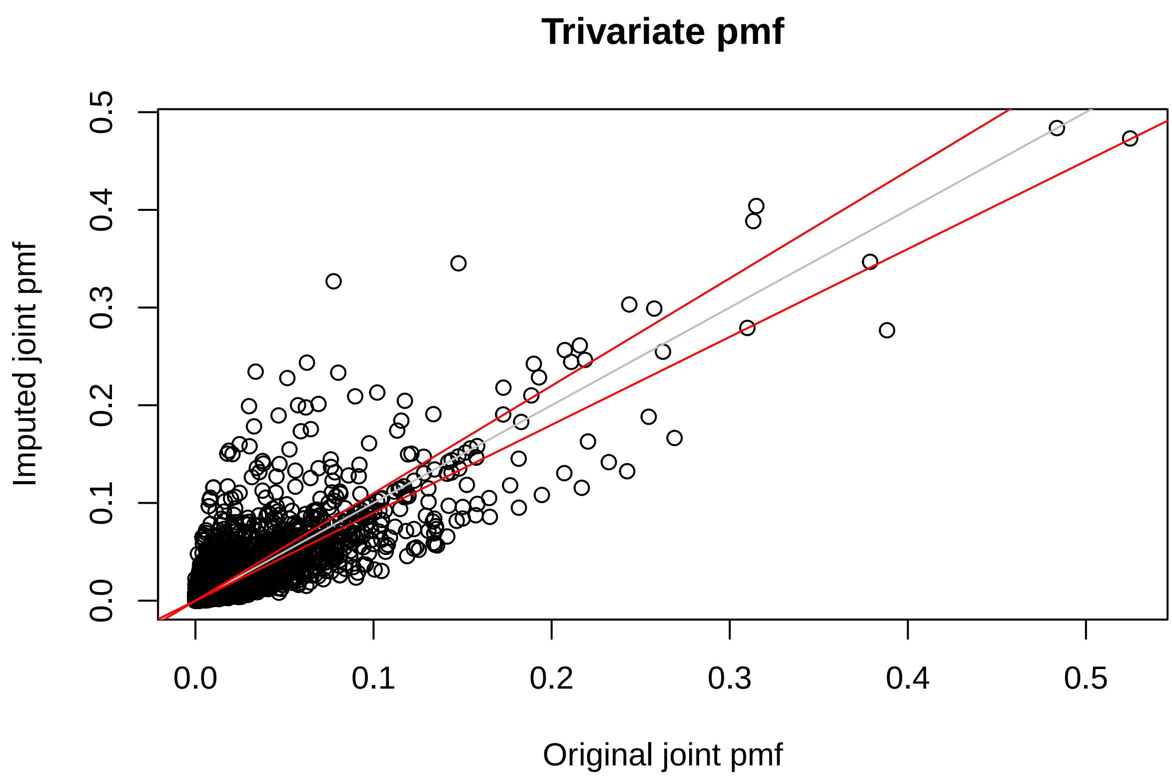

MICE: SCHL
original_pmf
observed_pmf
imputed_pmf
0.0
0.1
0.2
0.3
0.4
1
2
3
4
5
6
7
Category


MICE: AGEP
original_pmf
observed_pmf
imputed_pmf
0.00
0.04
0.08
0.12
1
2
3
4
5
6
7
8
9
10
12
14
16
Category


MICE: WKL
original_pmf
observed_pmf
imputed_pmf
0.0
0.1
0.2
0.3
0.4
0.5
0.6
1
2
3
Category


MICE: PINCP
original_pmf
observed_pmf
imputed_pmf
0.00
0.10
0.20
0.30
1
2
3
4
5
6
7
8
9
10
11
12
13
Category


Bivariate pmf
Imputed joint pmf
Original joint pmf
0.0
0.2
0.4
0.6
0.8


Trivariate pmf
Imputed joint pmf
Original joint pmf
0.0
0.1
0.2
0.3
0.4
0.5