## The dance of the mechanisms: $\beta_X$ and $\beta_Y$

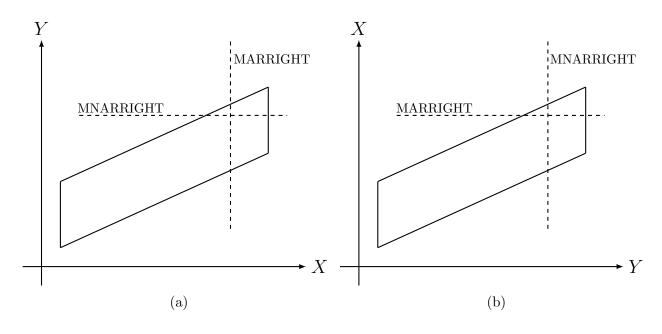
Method 1: We perform a model-based simulation by repeatedly drawing N=1,000 cases from a bivariate normal distribution with mvrnorm in the package MASS with mean vector  $\{5,5\}$  and we vary the correlation between X and Y with  $\rho$  in  $\{0.1,0.2,\ldots,0.9\}$ . We induce missingness in variable Y. Variable Y is regressed on X ( $Y \sim X$ ). Number of replications is 100. Evaluation of  $\beta_X$ .

Results 1: Figures 2 to 4. Bias in  $\beta_X$  increases when data correlations increase from  $\rho = 0.1$  to  $\rho = 0.6$ . Then, the bias decreases when data correlations increase more to  $\rho = 0.9$ . The coverage rate stabilizes when  $\rho \geq 0.6$ . With CCA, MAR mechanisms do not seem to effect  $\beta_X$ , but MNAR mechanisms do (see Figure 1a).

Method 2: Same data as above. We induce missingness in variable Y. But! Variable X is regressed on Y ( $X \sim Y$ ). Evaluation of  $\beta_Y$ .

Results 2: Here, Figure 1b applies. Since the missingness is in Y, MNAR mechanisms do not effect  $\beta_Y$  with CCA. MAR mechanisms on the other hand will affect  $\beta_Y$ . This is visible in Figures 5 to 7. Note that although MNAR mechanisms do not give bias with CCA, they do give bias (and low coverage) after MI!! Apparently the wrong value are imputed?

Conclusion: To know the effect of a missingness mechanism on a  $\beta$  coefficient, it is important to know whether the missing values are in the dependent or independent variable.



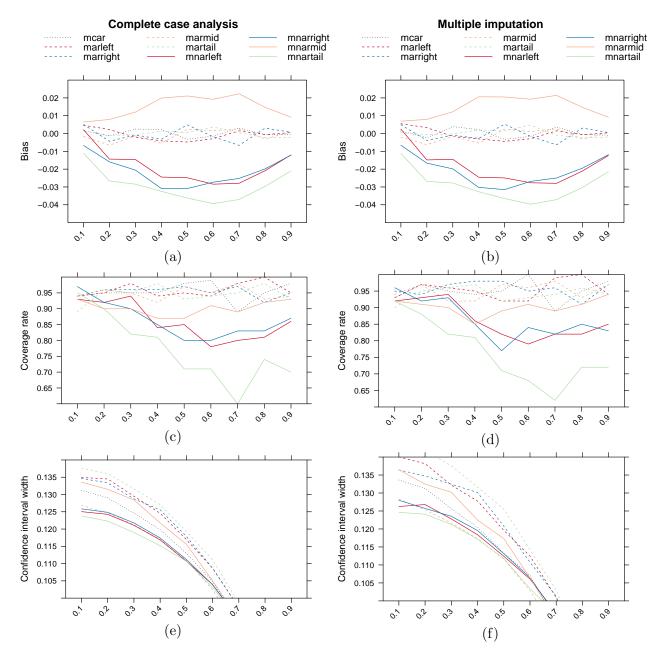


Figure 2: Coverage rate, average bias and average confidence interval width of  $\beta_X$  for complete case analysis and multiple imputation by Bayesian linear regression imputation. The x-axis displays the correlations between X and Y for all  $\rho$  in  $\{0.1, 0.2, \ldots, 0.9\}$ . Missingness proportion is 0.1.

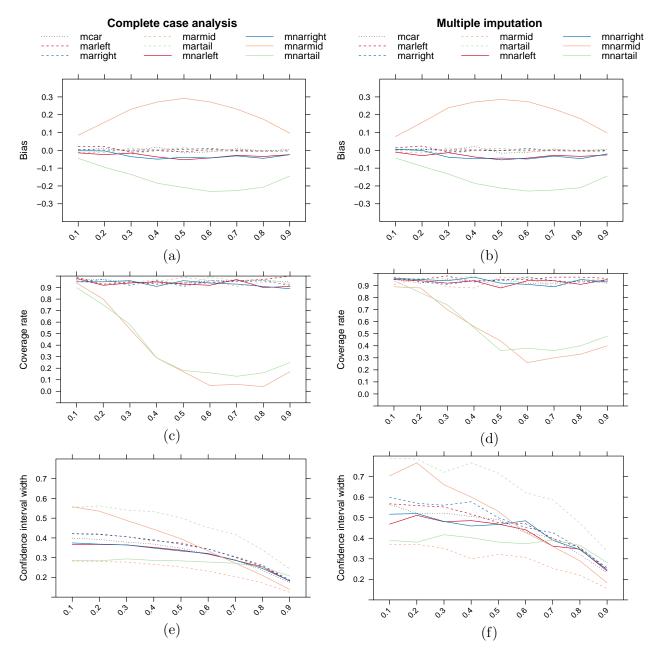


Figure 3: Coverage rate, average bias and average confidence interval width of  $\beta_X$  for complete case analysis and multiple imputation by Bayesian linear regression imputation. The x-axis displays the correlations between X and Y for all  $\rho$  in  $\{0.1, 0.2, \ldots, 0.9\}$ . Missingness proportion is 0.9.

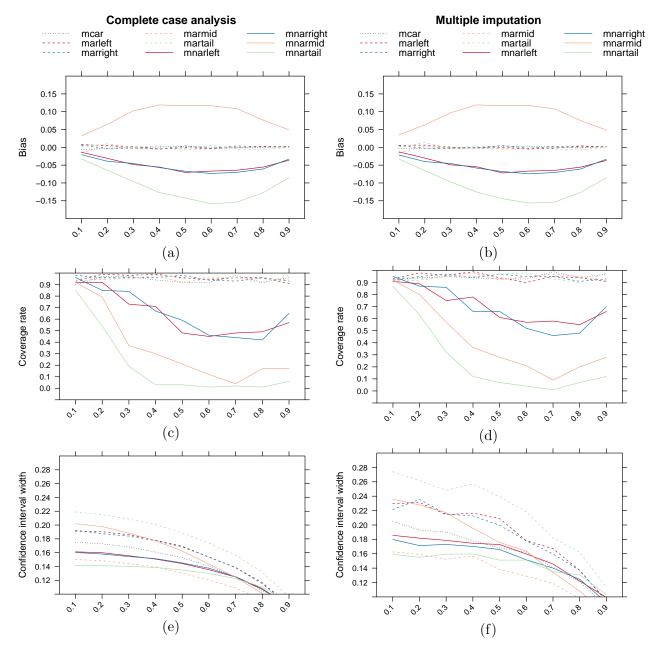


Figure 4: Coverage rate, average bias and average confidence interval width of  $\beta_X$  for complete case analysis and multiple imputation by Bayesian linear regression imputation. The x-axis displays the correlations between X and Y for all  $\rho$  in  $\{0.1, 0.2, \ldots, 0.9\}$ . Missingness proportion is 0.5.

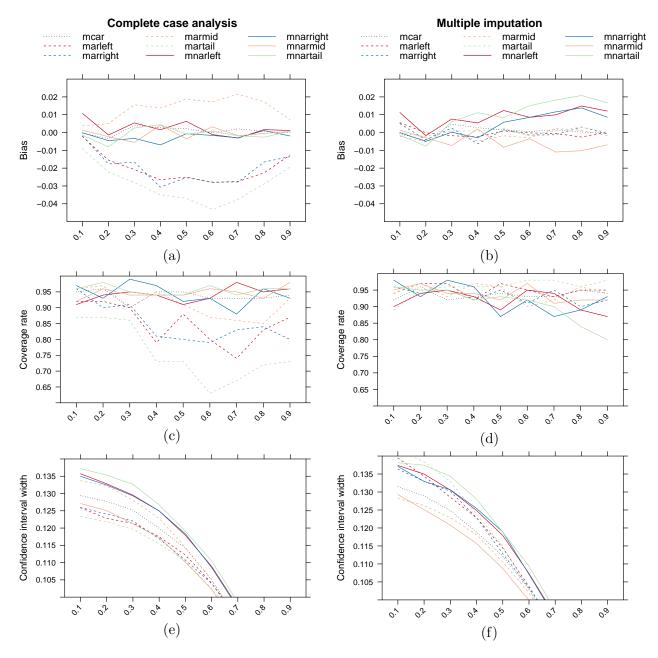


Figure 5: Coverage rate, average bias and average confidence interval width of  $\beta_Y$  for complete case analysis and multiple imputation by Bayesian linear regression imputation. The x-axis displays the correlations between X and Y for all  $\rho$  in  $\{0.1, 0.2, \ldots, 0.9\}$ . Missingness proportion is 0.1.

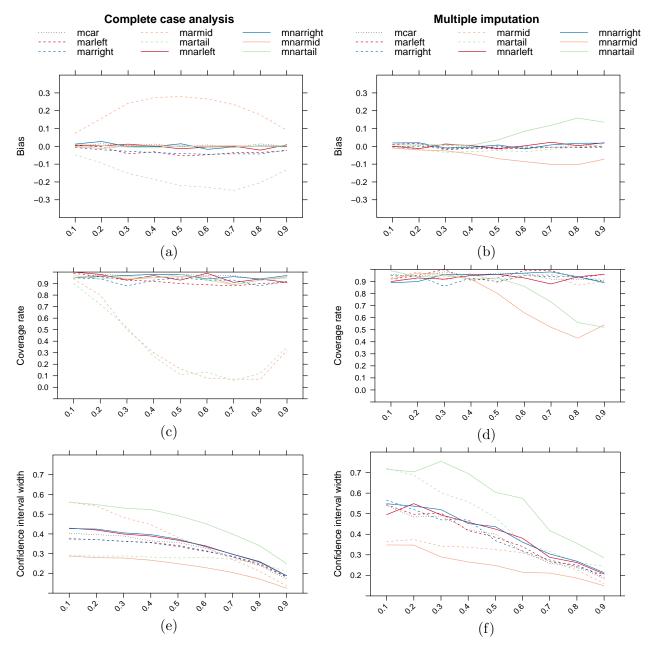


Figure 6: Coverage rate, average bias and average confidence interval width of  $\beta_Y$  for complete case analysis and multiple imputation by Bayesian linear regression imputation. The x-axis displays the correlations between X and Y for all  $\rho$  in  $\{0.1, 0.2, \ldots, 0.9\}$ . Missingness proportion is 0.9.

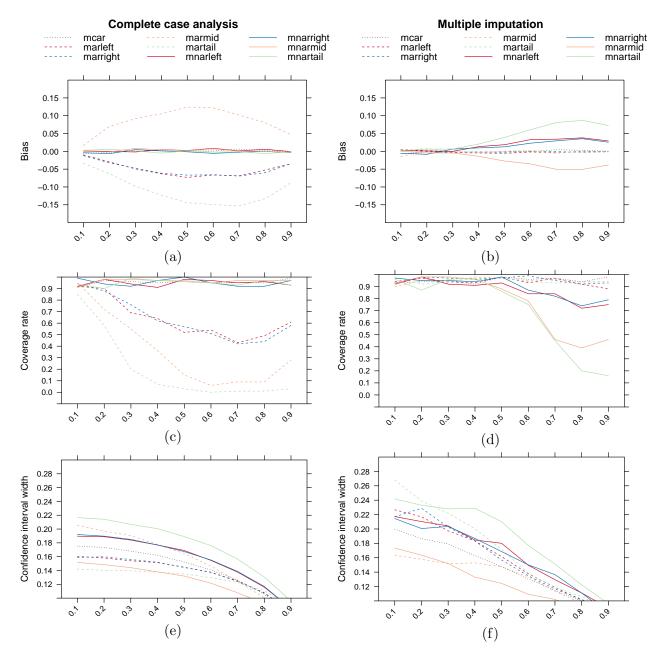


Figure 7: Coverage rate, average bias and average confidence interval width of  $\beta_Y$  for complete case analysis and multiple imputation by Bayesian linear regression imputation. The x-axis displays the correlations between X and Y for all  $\rho$  in  $\{0.1, 0.2, \ldots, 0.9\}$ . Missingness proportion is 0.5.