

# Package ‘multibias’

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**Type** Package

**Title** Simultaneous Multi-Bias Adjustment

**Version** 1.6

**Maintainer** Paul Brendel <pcbrendel@gmail.com>

**Description** Quantify the causal effect of a binary exposure on a binary outcome with adjustment for multiple biases. The functions can simultaneously adjust for any combination of uncontrolled confounding, exposure/outcome misclassification, and selection bias. The underlying method generalizes the concept of combining inverse probability of selection weighting with predictive value weighting. Simultaneous multi-bias analysis can be used to enhance the validity and transparency of real-world evidence obtained from observational, longitudinal studies. Based on the work from Paul Brendel, Aracelis Torres, and Onyebuchi Arah (2023) <doi:10.1093/ije/dyad001>.

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**Suggests** knitr, rmarkdown, testthat (>= 3.0.0)

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**BugReports** <https://github.com/pcbrendel/multibias/issues>

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**Author** Paul Brendel [aut, cre, cph]

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adjust_em	<i>Adjust for exposure misclassification.</i>
-----------	---

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### Description

adjust\_em returns the exposure-outcome odds ratio and confidence interval, adjusted for exposure misclassification.

### Usage

```
adjust_em(
  data_observed,
  data_validation = NULL,
  x_model_coefs = NULL,
  level = 0.95
)
```

### Arguments

data_observed	Object of class data_observed corresponding to the data to perform bias analysis on.
data_validation	Object of class data_validation corresponding to the validation data used to adjust for bias in the observed data. Here, the validation data should have data for the same variables as in the observed data, plus data for the true and misclassified exposure corresponding to the observed exposure in data_observed.
x_model_coefs	The regression coefficients corresponding to the model: $\text{logit}(P(X = 1)) = \delta_0 + \delta_1 X^* + \delta_2 Y + \delta_{2+j} C_j$ , where $X$ represents the binary true exposure, $X^*$ is the binary misclassified exposure, $Y$ is the outcome, $C$ represents the vector of measured confounders (if any), and $j$ corresponds to the number of measured confounders. The number of parameters is therefore $3 + j$ .
level	Value from 0-1 representing the full range of the confidence interval. Default is 0.95.

### Details

Values for the regression coefficients can be applied as fixed values or as single draws from a probability distribution (ex: `rnorm(1, mean = 2, sd = 1)`). The latter has the advantage of allowing the researcher to capture the uncertainty in the bias parameter estimates. To incorporate this uncertainty in the estimate and confidence interval, this function should be run in loop across bootstrap samples of the dataframe for analysis. The estimate and confidence interval would then be obtained from the median and quantiles of the distribution of odds ratio estimates.

### Value

A list where the first item is the odds ratio estimate of the effect of the exposure on the outcome and the second item is the confidence interval as the vector: (lower bound, upper bound).

**Examples**

```

df_observed <- data_observed(
  data = df_em,
  exposure = "Xstar",
  outcome = "Y",
  confounders = "C1"
)

# Using validation data -----
df_validation <- data_validation(
  data = df_em_source,
  true_exposure = "X",
  true_outcome = "Y",
  confounders = "C1",
  misclassified_exposure = "Xstar"
)

adjust_em(
  data_observed = df_observed,
  data_validation = df_validation
)

# Using x_model_coefs -----
adjust_em(
  data_observed = df_observed,
  x_model_coefs = c(-2.10, 1.62, 0.63, 0.35)
)

```

---

adjust\_em\_om

*Adjust for exposure misclassification and outcome misclassification.*


---

**Description**

adjust\_em\_om returns the exposure-outcome odds ratio and confidence interval, adjusted for exposure misclassification and outcome misclassification. Two different options for the bias parameters are available here: 1) parameters from separate models of  $X$  and  $Y$  (`x_model_coefs` and `y_model_coefs`) or 2) parameters from a joint model of  $X$  and  $Y$  (`x1y0_model_coefs`, `x0y1_model_coefs`, and `x1y1_model_coefs`).

**Usage**

```

adjust_em_om(
  data_observed,
  x_model_coefs = NULL,
  y_model_coefs = NULL,
  x1y0_model_coefs = NULL,
  x0y1_model_coefs = NULL,
  x1y1_model_coefs = NULL,

```

```

    level = 0.95
  )

```

### Arguments

- data\_observed** Object of class `data_observed` corresponding to the data to perform bias analysis on.
- x\_model\_coefs** The regression coefficients corresponding to the model:  $\text{logit}(P(X = 1)) = \delta_0 + \delta_1 X^* + \delta_2 Y^* + \delta_2 + jC_j$ , where  $X$  represents the binary true exposure,  $X^*$  is the binary misclassified exposure,  $Y^*$  is the binary misclassified outcome,  $C$  represents the vector of measured confounders (if any), and  $j$  corresponds to the number of measured confounders. The number of parameters is therefore  $3 + j$ .
- y\_model\_coefs** The regression coefficients corresponding to the model:  $\text{logit}(P(Y = 1)) = \beta_0 + \beta_1 X + \beta_2 Y^* + \beta_2 + jC_j$ , where  $Y$  represents the binary true exposure,  $X$  is the binary exposure,  $Y$  is the binary misclassified outcome,  $C$  represents the vector of measured confounders (if any), and  $j$  corresponds to the number of measured confounders. The number of parameters is therefore  $3 + j$ .
- x1y0\_model\_coefs** The regression coefficients corresponding to the model:  $\log(P(X = 1, Y = 0)/P(X = 0, Y = 0)) = \gamma_{1,0} + \gamma_{1,1}X^* + \gamma_{1,2}Y^* + \gamma_{1,2+j}C_j$ , where  $X$  is the binary true exposure,  $Y$  is the binary true outcome,  $X^*$  is the binary misclassified exposure,  $Y^*$  is the binary misclassified outcome,  $C$  represents the vector of measured confounders (if any), and  $j$  corresponds to the number of measured confounders.
- x0y1\_model\_coefs** The regression coefficients corresponding to the model:  $\log(P(X = 0, U = 1)/P(X = 0, U = 0)) = \gamma_{2,0} + \gamma_{2,1}X^* + \gamma_{2,2}Y^* + \gamma_{2,2+j}C_j$ , where  $X$  is the binary true exposure,  $Y$  is the binary true outcome,  $X^*$  is the binary misclassified exposure,  $Y^*$  is the binary misclassified outcome,  $C$  represents the vector of measured confounders (if any), and  $j$  corresponds to the number of measured confounders.
- x1y1\_model\_coefs** The regression coefficients corresponding to the model:  $\log(P(X = 1, Y = 1)/P(X = 0, Y = 0)) = \gamma_{3,0} + \gamma_{3,1}X^* + \gamma_{3,2}Y^* + \gamma_{3,2+j}C_j$ , where  $X$  is the binary true exposure,  $Y$  is the binary true outcome,  $X^*$  is the binary misclassified exposure,  $Y^*$  is the binary misclassified outcome,  $C$  represents the vector of measured confounders (if any), and  $j$  corresponds to the number of measured confounders.
- level** Value from 0-1 representing the full range of the confidence interval. Default is 0.95.

### Details

Values for the regression coefficients can be applied as fixed values or as single draws from a probability distribution (ex: `rnorm(1, mean = 2, sd = 1)`). The latter has the advantage of allowing the researcher to capture the uncertainty in the bias parameter estimates. To incorporate this uncertainty in the estimate and confidence interval, this function should be run in loop across bootstrap samples of the dataframe for analysis. The estimate and confidence interval would then be obtained from the median and quantiles of the distribution of odds ratio estimates.

**Value**

A list where the first item is the odds ratio estimate of the effect of the exposure on the outcome and the second item is the confidence interval as the vector: (lower bound, upper bound).

**Examples**

```
df <- data_observed(
  data = df_em_om,
  exposure = "Xstar",
  outcome = "Ystar",
  confounders = "C1"
)

# Using x_model_coefs and y_model_coefs -----
adjust_em_om(
  df,
  x_model_coefs = c(-2.15, 1.64, 0.35, 0.38),
  y_model_coefs = c(-3.10, 0.63, 1.60, 0.39)
)

# Using x1y0_model_coefs, x0y1_model_coefs, and x1y1_model_coefs -----
adjust_em_om(
  df,
  x1y0_model_coefs = c(-2.18, 1.63, 0.23, 0.36),
  x0y1_model_coefs = c(-3.17, 0.22, 1.60, 0.40),
  x1y1_model_coefs = c(-4.76, 1.82, 1.83, 0.72)
)
```

---

adjust\_em\_sel

*Adust for exposure misclassification and selection bias.*


---

**Description**

adjust\_em\_sel returns the exposure-outcome odds ratio and confidence interval, adjusted for exposure misclassification and selection bias.

**Usage**

```
adjust_em_sel(data_observed, x_model_coefs, s_model_coefs, level = 0.95)
```

**Arguments**

**data\_observed** Object of class data\_observed corresponding to the data to perform bias analysis on.

**x\_model\_coefs** The regression coefficients corresponding to the model:  $\text{logit}(P(X = 1)) = \delta_0 + \delta_1 X^* + \delta_2 Y + \delta_2 + jC_j$ , where  $X$  represents the binary true exposure,  $X^*$  is the binary misclassified exposure,  $Y$  is the outcome,  $C$  represents the vector

	of measured confounders (if any), and $j$ corresponds to the number of measured confounders. The number of parameters is therefore $3 + j$ .
s_model_coefs	The regression coefficients corresponding to the model: $\text{logit}(P(S = 1)) = \beta_0 + \beta_1 X^* + \beta_2 Y + \beta_3 + jC_j$ , where $S$ represents binary selection, $X^*$ is the binary misclassified exposure, $Y$ is the outcome, $C$ represents the vector of measured confounders (if any), and $j$ corresponds to the number of measured confounders. The number of parameters is therefore $3 + j$ .
level	Value from 0-1 representing the full range of the confidence interval. Default is 0.95.

### Details

Values for the regression coefficients can be applied as fixed values or as single draws from a probability distribution (ex: `rnorm(1, mean = 2, sd = 1)`). The latter has the advantage of allowing the researcher to capture the uncertainty in the bias parameter estimates. To incorporate this uncertainty in the estimate and confidence interval, this function should be run in loop across bootstrap samples of the dataframe for analysis. The estimate and confidence interval would then be obtained from the median and quantiles of the distribution of odds ratio estimates.

### Value

A list where the first item is the odds ratio estimate of the effect of the exposure on the outcome and the second item is the confidence interval as the vector: (lower bound, upper bound).

### Examples

```
df <- data_observed(
  data = df_em_sel,
  exposure = "Xstar",
  outcome = "Y",
  confounders = "C1"
)
adjust_em_sel(
  df,
  x_model_coefs = c(-2.78, 1.62, 0.58, 0.34),
  s_model_coefs = c(0.04, 0.18, 0.92, 0.05)
)
```

---

adjust\_om

*Adjust for outcome misclassification.*

---

### Description

adjust\_om returns the exposure-outcome odds ratio and confidence interval, adjusted for outcome misclassification.

**Usage**

```
adjust_om(
  data_observed,
  data_validation = NULL,
  y_model_coefs = NULL,
  level = 0.95
)
```

**Arguments**

**data\_observed** Object of class `data_observed` corresponding to the data to perform bias analysis on.

**data\_validation** Object of class `data_validation` corresponding to the validation data used to adjust for bias in the observed data. Here, the validation data should have data for the same variables as in the observed data, plus data for the true and misclassified outcome corresponding to the observed outcome in `data_observed`.

**y\_model\_coefs** The regression coefficients corresponding to the model:  $\text{logit}(P(Y = 1)) = \_delta_0 + \_delta_1 X + \_delta_2 Y^* + \_delta_{2+j} C_j$ , where  $Y$  represents the binary true outcome,  $X$  is the exposure,  $Y^*$  is the binary misclassified outcome,  $C$  represents the vector of measured confounders (if any), and  $j$  corresponds to the number of measured confounders. The number of parameters is therefore  $3 + j$ .

**level** Value from 0-1 representing the full range of the confidence interval. Default is 0.95.

**Details**

Values for the regression coefficients can be applied as fixed values or as single draws from a probability distribution (ex: `rnorm(1, mean = 2, sd = 1)`). The latter has the advantage of allowing the researcher to capture the uncertainty in the bias parameter estimates. To incorporate this uncertainty in the estimate and confidence interval, this function should be run in loop across bootstrap samples of the dataframe for analysis. The estimate and confidence interval would then be obtained from the median and quantiles of the distribution of odds ratio estimates.

**Value**

A list where the first item is the odds ratio estimate of the effect of the exposure on the outcome and the second item is the confidence interval as the vector: (lower bound, upper bound).

**Examples**

```
df_observed <- data_observed(
  data = df_om,
  exposure = "X",
  outcome = "Ystar",
  confounders = "C1"
)
# Using validation data -----
df_validation <- data_validation(
```



```

    data = df_om_source,
    true_exposure = "X",
    true_outcome = "Y",
    confounders = "C1",
    misclassified_outcome = "Ystar"
  )

adjust_om(
  data_observed = df_observed,
  data_validation = df_validation
)

# Using y_model_coefs -----
adjust_om(
  data_observed = df_observed,
  y_model_coefs = c(-3.1, 0.6, 1.6, 0.4)
)

```

---

adjust\_om\_sel

*Adjust for outcome misclassification and selection bias.*


---

## Description

adjust\_om\_sel returns the exposure-outcome odds ratio and confidence interval, adjusted for outcome misclassification and selection bias.

## Usage

```
adjust_om_sel(data_observed, y_model_coefs, s_model_coefs, level = 0.95)
```

## Arguments

- |               |   |
|---------------|---|
| data_observed | Object of class data_observed corresponding to the data to perform bias analysis on.  |
| y_model_coefs | The regression coefficients corresponding to the model: $\text{logit}(P(Y = 1)) = \delta_0 + \delta_1 X + \delta_2 Y^* + \delta_{2+j} C_j$ , where $Y$ represents the binary true outcome, $X$ is the exposure, $Y^*$ is the binary misclassified outcome, $C$ represents the vector of measured confounders (if any), and $j$ corresponds to the number of measured confounders. The number of parameters is therefore $3 + j$ . |
| s_model_coefs | The regression coefficients corresponding to the model: $\text{logit}(P(S = 1)) = \beta_0 + \beta_1 X + \beta_2 Y^* + \beta_{2+j} C_j$ , where $S$ represents binary selection, $X$ is the exposure, $Y^*$ is the binary misclassified outcome, $C$ represents the vector of measured confounders (if any), and $j$ corresponds to the number of measured confounders. The number of parameters is therefore $3 + j$ .            |
| level         | Value from 0-1 representing the full range of the confidence interval. Default is 0.95.   |

## Details

Values for the regression coefficients can be applied as fixed values or as single draws from a probability distribution (ex: `rnorm(1, mean = 2, sd = 1)`). The latter has the advantage of allowing the researcher to capture the uncertainty in the bias parameter estimates. To incorporate this uncertainty in the estimate and confidence interval, this function should be run in loop across bootstrap samples of the dataframe for analysis. The estimate and confidence interval would then be obtained from the median and quantiles of the distribution of odds ratio estimates.

## Value

A list where the first item is the odds ratio estimate of the effect of the exposure on the outcome and the second item is the confidence interval as the vector: (lower bound, upper bound).

## Examples

```
df <- data_observed(  
  data = df_om_sel,  
  exposure = "X",  
  outcome = "Ystar",  
  confounders = "C1"  
)  
adjust_om_sel(  
  df,  
  y_model_coefs = c(-3.24, 0.58, 1.59, 0.45),  
  s_model_coefs = c(0.03, 0.92, 0.12, 0.05)  
)
```

---

adjust\_sel

*Adjust for selection bias.*

---

## Description

adjust\_sel returns the exposure-outcome odds ratio and confidence interval, adjusted for selection bias.

## Usage

```
adjust_sel(  
  data_observed,  
  data_validation = NULL,  
  s_model_coefs = NULL,  
  level = 0.95  
)
```

**Arguments**

data_observed	Object of class data_observed corresponding to the data to perform bias analysis on.
data_validation	Object of class data_validation corresponding to the validation data used to adjust for bias in the observed data. Here, the validation data should have data for the same variables as in the observed data, plus data for the selection indicator representing whether the observation was selected in data_observed.
s_model_coefs	The regression coefficients corresponding to the model: $\text{logit}(P(S = 1)) = \beta_0 + \beta_1 X + \beta_2 Y$ , where $S$ represents binary selection, $X$ is the exposure, and $Y$ is the outcome. The number of parameters is therefore 3.
level	Value from 0-1 representing the full range of the confidence interval. Default is 0.95.

**Details**

Values for the regression coefficients can be applied as fixed values or as single draws from a probability distribution (ex: `rnorm(1, mean = 2, sd = 1)`). The latter has the advantage of allowing the researcher to capture the uncertainty in the bias parameter estimates. To incorporate this uncertainty in the estimate and confidence interval, this function should be run in loop across bootstrap samples of the dataframe for analysis. The estimate and confidence interval would then be obtained from the median and quantiles of the distribution of odds ratio estimates.

**Value**

A list where the first item is the odds ratio estimate of the effect of the exposure on the outcome and the second item is the confidence interval as the vector: (lower bound, upper bound).

**Examples**

```
df_observed <- data_observed(
  data = df_sel,
  exposure = "X",
  outcome = "Y",
  confounders = "C1"
)

# Using validation data -----
df_validation <- data_validation(
  data = df_sel_source,
  true_exposure = "X",
  true_outcome = "Y",
  confounders = "C1",
  selection = "S"
)

adjust_sel(
  data_observed = df_observed,
  data_validation = df_validation
```

```

)

# Using s_model_coefs -----
adjust_sel(
  data_observed = df_observed,
  s_model_coefs = c(0, 0.9, 0.9)
)

```

---

adjust\_uc

*Adjust for uncontrolled confounding.*


---

### Description

adjust\_uc returns the exposure-outcome odds ratio and confidence interval, adjusted for uncontrolled confounding from a binary confounder.

### Usage

```

adjust_uc(
  data_observed,
  data_validation = NULL,
  u_model_coefs = NULL,
  level = 0.95
)

```

### Arguments

**data\_observed** Object of class `data_observed` corresponding to the data to perform bias analysis on.

**data\_validation** Object of class `data_validation` corresponding to the validation data used to adjust for bias in the observed data. Here, the validation data should have data for the same variables as in the observed data, plus data for the confounder missing in `data_observed`.

**u\_model\_coefs** The regression coefficients corresponding to the model:  $\text{logit}(P(U = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 Y + \alpha_{2+j} C_j$ , where  $U$  is the binary unmeasured confounder,  $X$  is the exposure,  $Y$  is the outcome,  $C$  represents the vector of measured confounders (if any), and  $j$  corresponds to the number of measured confounders. The number of parameters therefore equals  $3 + j$ .

**level** Value from 0-1 representing the full range of the confidence interval. Default is 0.95.

## Details

Values for the regression coefficients can be applied as fixed values or as single draws from a probability distribution (ex: `rnorm(1, mean = 2, sd = 1)`). The latter has the advantage of allowing the researcher to capture the uncertainty in the bias parameter estimates. To incorporate this uncertainty in the estimate and confidence interval, this function should be run in loop across bootstrap samples of the dataframe for analysis. The estimate and confidence interval would then be obtained from the median and quantiles of the distribution of odds ratio estimates.

## Value

A list where the first item is the odds ratio estimate of the effect of the exposure on the outcome and the second item is the confidence interval as the vector: (lower bound, upper bound).

## Examples

```
df_observed <- data_observed(
  data = df_uc,
  exposure = "X_bi",
  outcome = "Y_bi",
  confounders = c("C1", "C2", "C3")
)

# Using validation data -----
df_validation <- data_validation(
  data = df_uc_source,
  true_exposure = "X_bi",
  true_outcome = "Y_bi",
  confounders = c("C1", "C2", "C3", "U")
)

adjust_uc(
  data_observed = df_observed,
  data_validation = df_validation
)

# Using u_model_coefs -----
adjust_uc(
  data_observed = df_observed,
  u_model_coefs = c(-0.19, 0.61, 0.70, -0.09, 0.10, -0.15)
)
```

## Description

adjust\_uc\_em returns the exposure-outcome odds ratio and confidence interval, adjusted for uncontrolled confounding and exposure misclassification. Two different options for the bias parameters are available here: 1) parameters from separate models of  $U$  and  $X$  (u\_model\_coefs and x\_model\_coefs) or 2) parameters from a joint model of  $U$  and  $X$  (x1u0\_model\_coefs, x0u1\_model\_coefs, and x1u1\_model\_coefs).

## Usage

```
adjust_uc_em(
  data_observed,
  u_model_coefs = NULL,
  x_model_coefs = NULL,
  x1u0_model_coefs = NULL,
  x0u1_model_coefs = NULL,
  x1u1_model_coefs = NULL,
  level = 0.95
)
```

## Arguments

- data\_observed    Object of class data\_observed corresponding to the data to perform bias analysis on.
- u\_model\_coefs    The regression coefficients corresponding to the model:  $\text{logit}(P(U = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 Y$ , where  $U$  is the binary unmeasured confounder,  $X$  is the binary true exposure, and  $Y$  is the outcome. The number of parameters therefore equals 3.
- x\_model\_coefs    The regression coefficients corresponding to the model:  $\text{logit}(P(X = 1)) = \delta_0 + \delta_1 X^* + \delta_2 Y + \delta_{2+j} C_j$ , where  $X$  represents the binary true exposure,  $X^*$  is the binary misclassified exposure,  $Y$  is the outcome, and  $C$  represents the vector of measured confounders (if any), and  $j$  corresponds to the number of measured confounders. The number of parameters therefore equals  $3 + j$ .
- x1u0\_model\_coefs    The regression coefficients corresponding to the model:  $\log(P(X = 1, U = 0)/P(X = 0, U = 0)) = \gamma_{1,0} + \gamma_{1,1} X^* + \gamma_{1,2} Y + \gamma_{1,2+j} C_j$ , where  $X$  is the binary true exposure,  $U$  is the binary unmeasured confounder,  $X^*$  is the binary misclassified exposure,  $Y$  is the outcome,  $C$  represents the vector of measured confounders (if any), and  $j$  corresponds to the number of measured confounders.
- x0u1\_model\_coefs    The regression coefficients corresponding to the model:  $\log(P(X = 0, U = 1)/P(X = 0, U = 0)) = \gamma_{2,0} + \gamma_{2,1} X^* + \gamma_{2,2} Y + \gamma_{2,2+j} C_j$ , where  $X$  is the binary true exposure,  $U$  is the binary unmeasured confounder,  $X^*$  is the binary misclassified exposure,  $Y$  is the outcome,  $C$  represents the vector of measured confounders (if any), and  $j$  corresponds to the number of measured confounders.
- x1u1\_model\_coefs    The regression coefficients corresponding to the model:  $\log(P(X = 1, U = 1)/P(X = 0, U = 0)) = \gamma_{3,0} + \gamma_{3,1} X^* + \gamma_{3,2} Y + \gamma_{3,2+j} C_j$ , where  $X$  is the

binary true exposure,  $U$  is the binary unmeasured confounder,  $X^*$  is the binary misclassified exposure,  $Y$  is the outcome,  $C$  represents the vector of measured confounders (if any), and  $j$  corresponds to the number of measured confounders.

level Value from 0-1 representing the full range of the confidence interval. Default is 0.95.

### Details

Values for the regression coefficients can be applied as fixed values or as single draws from a probability distribution (ex: `rnorm(1, mean = 2, sd = 1)`). The latter has the advantage of allowing the researcher to capture the uncertainty in the bias parameter estimates. To incorporate this uncertainty in the estimate and confidence interval, this function should be run in loop across bootstrap samples of the dataframe for analysis. The estimate and confidence interval would then be obtained from the median and quantiles of the distribution of odds ratio estimates.

### Value

A list where the first item is the odds ratio estimate of the effect of the exposure on the outcome and the second item is the confidence interval as the vector: (lower bound, upper bound).

### Examples

```
df <- data_observed(
  data = df_uc_em,
  exposure = "Xstar",
  outcome = "Y",
  confounders = "C1"
)
# Using u_model_coefs and x_model_coefs -----
adjust_uc_em(
  df,
  u_model_coefs = c(-0.23, 0.63, 0.66),
  x_model_coefs = c(-2.47, 1.62, 0.73, 0.32)
)

# Using x1u0_model_coefs, x0u1_model_coefs, x1u1_model_coefs -----
adjust_uc_em(
  df,
  x1u0_model_coefs = c(-2.82, 1.62, 0.68, -0.06),
  x0u1_model_coefs = c(-0.20, 0.00, 0.68, -0.05),
  x1u1_model_coefs = c(-2.36, 1.62, 1.29, 0.27)
)
```

---

adjust\_uc\_em\_sel

*Adjust for uncontrolled confounding, exposure misclassification, and selection bias.*

---

## Description

adjust\_uc\_em\_sel returns the exposure-outcome odds ratio and confidence interval, adjusted for uncontrolled confounding, exposure misclassification, and selection bias. Two different options for the bias parameters are available here: 1) parameters from separate models of  $U$  and  $X$  (u\_model\_coefs and x\_model\_coefs) or 2) parameters from a joint model of  $U$  and  $X$  (x1u0\_model\_coefs, x0u1\_model\_coefs, and x1u1\_model\_coefs). Both approaches require s\_model\_coefs.

## Usage

```
adjust_uc_em_sel(
  data_observed,
  u_model_coefs = NULL,
  x_model_coefs = NULL,
  x1u0_model_coefs = NULL,
  x0u1_model_coefs = NULL,
  x1u1_model_coefs = NULL,
  s_model_coefs,
  level = 0.95
)
```

## Arguments

- data\_observed** Object of class data\_observed corresponding to the data to perform bias analysis on.
- u\_model\_coefs** The regression coefficients corresponding to the model:  $\text{logit}(P(U = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 Y$ , where  $U$  is the binary unmeasured confounder,  $X$  is the binary true exposure, and  $Y$  is the outcome. The number of parameters therefore equals 3.
- x\_model\_coefs** The regression coefficients corresponding to the model:  $\text{logit}(P(X = 1)) = \delta_0 + \delta_1 X^* + \delta_2 Y + \delta_{2+j} C_j$ , where  $X$  represents binary true exposure,  $X^*$  is the binary misclassified exposure,  $Y$  is the outcome,  $C$  represents the vector of measured confounders (if any), and  $j$  corresponds to the number of measured confounders. The number of parameters therefore equals  $3 + j$ .
- x1u0\_model\_coefs** The regression coefficients corresponding to the model:  $\log(P(X = 1, U = 0)/P(X = 0, U = 0)) = \gamma_{1,0} + \gamma_{1,1} X^* + \gamma_{1,2} Y + \gamma_{1,2+j} C_j$ , where  $X$  is the binary true exposure,  $U$  is the binary unmeasured confounder,  $X^*$  is the binary misclassified exposure,  $Y$  is the outcome,  $C$  represents the vector of measured confounders (if any), and  $j$  corresponds to the number of measured confounders.
- x0u1\_model\_coefs** The regression coefficients corresponding to the model:  $\log(P(X = 0, U = 1)/P(X = 0, U = 0)) = \gamma_{2,0} + \gamma_{2,1} X^* + \gamma_{2,2} Y + \gamma_{2,2+j} C_j$ , where  $X$  is the binary true exposure,  $U$  is the binary unmeasured confounder,  $X^*$  is the binary misclassified exposure,  $Y$  is the outcome,  $C$  represents the vector of measured confounders (if any), and  $j$  corresponds to the number of measured confounders.
- x1u1\_model\_coefs** The regression coefficients corresponding to the model:  $\log(P(X = 1, U = 1)/P(X = 0, U = 0)) = \gamma_{3,0} + \gamma_{3,1} X^* + \gamma_{3,2} Y + \gamma_{3,2+j} C_j$ , where  $X$  is the



binary true exposure,  $U$  is the binary unmeasured confounder,  $X^*$  is the binary misclassified exposure,  $Y$  is the outcome,  $C$  represents the vector of measured confounders (if any), and  $j$  corresponds to the number of measured confounders.

- `s_model_coefs` The regression coefficients corresponding to the model:  $\text{logit}(P(S = 1)) = \beta_0 + \beta_1 X^* + \beta_2 Y + \beta_{2+j} C_j$ , where  $S$  represents binary selection,  $X^*$  is the binary misclassified exposure,  $Y$  is the outcome,  $C$  represents the vector of measured confounders (if any), and  $j$  corresponds to the number of measured confounders. The number of parameters therefore equals  $3 + j$ .
- `level` Value from 0-1 representing the full range of the confidence interval. Default is 0.95.

### Details

Values for the regression coefficients can be applied as fixed values or as single draws from a probability distribution (ex: `rnorm(1, mean = 2, sd = 1)`). The latter has the advantage of allowing the researcher to capture the uncertainty in the bias parameter estimates. To incorporate this uncertainty in the estimate and confidence interval, this function should be run in loop across bootstrap samples of the dataframe for analysis. The estimate and confidence interval would then be obtained from the median and quantiles of the distribution of odds ratio estimates.

### Value

A list where the first item is the odds ratio estimate of the effect of the exposure on the outcome and the second item is the confidence interval as the vector: (lower bound, upper bound).

### Examples

```
df <- data_observed(
  data = df_uc_em_sel,
  exposure = "Xstar",
  outcome = "Y",
  confounders = c("C1", "C2", "C3")
)
# Using u_model_coefs, x_model_coefs, s_model_coefs -----
adjust_uc_em_sel(
  df,
  u_model_coefs = c(-0.32, 0.59, 0.69),
  x_model_coefs = c(-2.44, 1.62, 0.72, 0.32, -0.15, 0.85),
  s_model_coefs = c(0.00, 0.26, 0.78, 0.03, -0.02, 0.10)
)

# Using x1u0_model_coefs, x0u1_model_coefs, x1u1_model_coefs, s_model_coefs
adjust_uc_em_sel(
  df,
  x1u0_model_coefs = c(-2.78, 1.62, 0.61, 0.36, -0.27, 0.88),
  x0u1_model_coefs = c(-0.17, -0.01, 0.71, -0.08, 0.07, -0.15),
  x1u1_model_coefs = c(-2.36, 1.62, 1.29, 0.25, -0.06, 0.74),
  s_model_coefs = c(0.00, 0.26, 0.78, 0.03, -0.02, 0.10)
)
```

adjust\_uc\_om

*Adjust for uncontrolled confounding and outcome misclassification.***Description**

adjust\_uc\_om returns the exposure-outcome odds ratio and confidence interval, adjusted for uncontrolled confounding and outcome misclassification. Two different options for the bias parameters are available here: 1) parameters from separate models of  $U$  and  $Y$  (u\_model\_coefs and y\_model\_coefs) or 2) parameters from a joint model of  $U$  and  $Y$  (u1y0\_model\_coefs, u0y1\_model\_coefs, and u1y1\_model\_coefs).

**Usage**

```
adjust_uc_om(
  data_observed,
  u_model_coefs = NULL,
  y_model_coefs = NULL,
  u1y0_model_coefs = NULL,
  u0y1_model_coefs = NULL,
  u1y1_model_coefs = NULL,
  level = 0.95
)
```

**Arguments**

- data\_observed** Object of class data\_observed corresponding to the data to perform bias analysis on.
- u\_model\_coefs** The regression coefficients corresponding to the model:  $\text{logit}(P(U = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 Y$ , where  $U$  is the binary unmeasured confounder,  $X$  is the exposure,  $Y$  is the binary true outcome. The number of parameters therefore equals 3.
- y\_model\_coefs** The regression coefficients corresponding to the model:  $\text{logit}(P(Y = 1)) = \delta_0 + \delta_1 X + \delta_2 Y^* + \delta_{2+j} C_j$ , where  $Y$  represents binary true outcome,  $X$  is the exposure,  $Y^*$  is the binary misclassified outcome,  $C$  represents the vector of measured confounders (if any), and  $j$  corresponds to the number of measured confounders. The number of parameters therefore equals  $3 + j$ .
- u1y0\_model\_coefs** The regression coefficients corresponding to the model:  $\log(P(U = 1, Y = 0)/P(U = 0, Y = 0)) = \gamma_{1,0} + \gamma_{1,1} X + \gamma_{1,2} Y^* + \gamma_{1,2+j} C_j$ , where  $U$  is the binary unmeasured confounder,  $Y$  is the binary true outcome,  $X$  is the exposure,  $Y^*$  is the binary misclassified outcome,  $C$  represents the vector of measured confounders (if any), and  $j$  corresponds to the number of measured confounders.
- u0y1\_model\_coefs** The regression coefficients corresponding to the model:  $\log(P(U = 0, Y = 1)/P(U = 0, Y = 0)) = \gamma_{2,0} + \gamma_{2,1} X + \gamma_{2,2} Y^* + \gamma_{2,2+j} C_j$ , where  $U$  is the binary unmeasured confounder,  $Y$  is the binary true outcome,  $X$  is the exposure,

$Y^*$  is the binary misclassified outcome,  $C$  represents the vector of measured confounders (if any), and  $j$  corresponds to the number of measured confounders.

u1y1\_model\_coefs

The regression coefficients corresponding to the model:  $\log(P(U = 1, Y = 1)/P(U = 0, Y = 0)) = \gamma_{3,0} + \gamma_{3,1}X + \gamma_{3,2}Y^* + \gamma_{3,2+j}C_j$ , where  $U$  is the binary unmeasured confounder,  $Y$  is the binary true outcome,  $X$  is the exposure,  $Y^*$  is the binary misclassified outcome,  $C$  represents the vector of measured confounders (if any), and  $j$  corresponds to the number of measured confounders.

level

Value from 0-1 representing the full range of the confidence interval. Default is 0.95.

## Details

Values for the regression coefficients can be applied as fixed values or as single draws from a probability distribution (ex: `rnorm(1, mean = 2, sd = 1)`). The latter has the advantage of allowing the researcher to capture the uncertainty in the bias parameter estimates. To incorporate this uncertainty in the estimate and confidence interval, this function should be run in loop across bootstrap samples of the dataframe for analysis. The estimate and confidence interval would then be obtained from the median and quantiles of the distribution of odds ratio estimates.

## Value

A list where the first item is the odds ratio estimate of the effect of the exposure on the outcome and the second item is the confidence interval as the vector: (lower bound, upper bound).

## Examples

```
df <- data_observed(
  data = df_uc_om,
  exposure = "X",
  outcome = "Ystar",
  confounders = "C1"
)
# Using u_model_coefs and y_model_coefs -----
adjust_uc_om(
  df,
  u_model_coefs = c(-0.22, 0.61, 0.70),
  y_model_coefs = c(-2.85, 0.73, 1.60, 0.38)
)

# Using u1y0_model_coefs, u0y1_model_coefs, u1y1_model_coefs -----
adjust_uc_om(
  df,
  u1y0_model_coefs = c(-0.19, 0.61, 0.00, -0.07),
  u0y1_model_coefs = c(-3.21, 0.60, 1.60, 0.36),
  u1y1_model_coefs = c(-2.72, 1.24, 1.59, 0.34)
)
```

---

adjust_uc_om_sel	<i>Adjust for uncontrolled confounding, outcome misclassification, and selection bias.</i>
------------------	--

---

### Description

adjust\_uc\_om\_sel returns the exposure-outcome odds ratio and confidence interval, adjusted for uncontrolled confounding, outcome misclassification, and selection bias. Two different options for the bias parameters are available here: 1) parameters from separate models of  $U$  and  $Y$  (u\_model\_coefs and y\_model\_coefs) or 2) parameters from a joint model of  $U$  and  $Y$  (u1y0\_model\_coefs, u0y1\_model\_coefs, and u1y1\_model\_coefs). Both approaches require s\_model\_coefs.

### Usage

```
adjust_uc_om_sel(
  data_observed,
  u_model_coefs = NULL,
  y_model_coefs = NULL,
  u0y1_model_coefs = NULL,
  u1y0_model_coefs = NULL,
  u1y1_model_coefs = NULL,
  s_model_coefs,
  level = 0.95
)
```

### Arguments

- data\_observed** Object of class data\_observed corresponding to the data to perform bias analysis on.
- u\_model\_coefs** The regression coefficients corresponding to the model:  $\text{logit}(P(U = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 Y$ , where  $U$  is the binary unmeasured confounder,  $X$  is the exposure, and  $Y$  is the binary true outcome. The number of parameters therefore equals 3.
- y\_model\_coefs** The regression coefficients corresponding to the model:  $\text{logit}(P(Y = 1)) = \delta_0 + \delta_1 X + \delta_2 Y^* + \delta_{2+j} C_j$ , where  $Y$  represents binary true outcome,  $X$  is the exposure,  $Y^*$  is the binary misclassified outcome,  $C$  represents the vector of measured confounders (if any), and  $j$  corresponds to the number of measured confounders. The number of parameters therefore equals  $3 + j$ .
- u0y1\_model\_coefs** The regression coefficients corresponding to the model:  $\log(P(U = 0, Y = 1)/P(U = 0, Y = 0)) = \gamma_{2,0} + \gamma_{2,1} X + \gamma_{2,2} Y^* + \gamma_{2,2+j} C_j$ , where  $U$  is the binary unmeasured confounder,  $Y$  is the binary true outcome,  $X$  is the exposure,  $Y^*$  is the binary misclassified outcome,  $C$  represents the vector of measured confounders (if any), and  $j$  corresponds to the number of measured confounders. The number of parameters therefore equals  $3 + j$ .

u1y0_model_coefs	The regression coefficients corresponding to the model: $\log(P(U = 1, Y = 0)/P(U = 0, Y = 0)) = \gamma_{1,0} + \gamma_{1,1}X + \gamma_{1,2}Y^* + \gamma_{1,2+j}C_j$ , where $U$ is the binary unmeasured confounder, $Y$ is the binary true outcome, $X$ is the exposure, $Y^*$ is the binary misclassified outcome, $C$ represents the vector of measured confounders (if any), and $j$ corresponds to the number of measured confounders. The number of parameters therefore equals $3 + j$ .
u1y1_model_coefs	The regression coefficients corresponding to the model: $\log(P(U = 1, Y = 1)/P(U = 0, Y = 0)) = \gamma_{3,0} + \gamma_{3,1}X + \gamma_{3,2}Y^* + \gamma_{3,2+j}C_j$ , where $U$ is the binary unmeasured confounder, $Y$ is the binary true outcome, $X$ is the exposure, $Y^*$ is the binary misclassified outcome, $C$ represents the vector of measured confounders (if any), and $j$ corresponds to the number of measured confounders. The number of parameters therefore equals $3 + j$ .
s_model_coefs	The regression coefficients corresponding to the model: $\text{logit}(P(S = 1)) = \beta_0 + \beta_1X + \beta_2Y^* + \beta_{2+j}C_j$ , where $S$ represents binary selection, $X$ is the exposure, $Y^*$ is the binary misclassified outcome, $C$ represents the vector of measured confounders (if any), and $j$ corresponds to the number of measured confounders. The number of parameters therefore equals $3 + j$ .
level	Value from 0-1 representing the full range of the confidence interval. Default is 0.95.

## Details

Values for the regression coefficients can be applied as fixed values or as single draws from a probability distribution (ex: `rnorm(1, mean = 2, sd = 1)`). The latter has the advantage of allowing the researcher to capture the uncertainty in the bias parameter estimates. To incorporate this uncertainty in the estimate and confidence interval, this function should be run in loop across bootstrap samples of the dataframe for analysis. The estimate and confidence interval would then be obtained from the median and quantiles of the distribution of odds ratio estimates.

## Value

A list where the first item is the odds ratio estimate of the effect of the exposure on the outcome and the second item is the confidence interval as the vector: (lower bound, upper bound).

## Examples

```
df <- data_observed(
  data = df_uc_om_sel,
  exposure = "X",
  outcome = "Ystar",
  confounders = c("C1", "C2", "C3")
)
# Using u_model_coefs, y_model_coefs, s_model_coefs -----
adjust_uc_om_sel(
  df,
  u_model_coefs = c(-0.32, 0.59, 0.69),
  y_model_coefs = c(-2.85, 0.71, 1.63, 0.40, -0.85, 0.22),
```

```

s_model_coefs = c(0.00, 0.74, 0.19, 0.02, -0.06, 0.02)
)

# Using u1y0_model_coefs, u0y1_model_coefs, u1y1_model_coefs, s_model_coefs
adjust_uc_om_sel(
  df,
  u1y0_model_coefs = c(-0.20, 0.62, 0.01, -0.08, 0.10, -0.15),
  u0y1_model_coefs = c(-3.28, 0.63, 1.65, 0.42, -0.85, 0.26),
  u1y1_model_coefs = c(-2.70, 1.22, 1.64, 0.32, -0.77, 0.09),
  s_model_coefs = c(0.00, 0.74, 0.19, 0.02, -0.06, 0.02)
)

```

---

adjust\_uc\_sel

*Adust for uncontrolled confounding and selection bias.*


---

### Description

adjust\_uc\_sel returns the exposure-outcome odds ratio and confidence interval, adjusted for uncontrolled confounding and exposure misclassification.

### Usage

```
adjust_uc_sel(data_observed, u_model_coefs, s_model_coefs, level = 0.95)
```

### Arguments

- |               |   |
|---------------|---|
| data_observed | Object of class data_observed corresponding to the data to perform bias analysis on.  |
| u_model_coefs | The regression coefficients corresponding to the model: $\text{logit}(P(U = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 Y + \alpha_{2+j} C_j$ , where $U$ is the binary unmeasured confounder, $X$ is the exposure, $Y$ is the outcome, $C$ represents the vector of measured confounders (if any), and $j$ corresponds to the number of measured confounders. The number of parameters therefore equals $3 + j$ . |
| s_model_coefs | The regression coefficients corresponding to the model: $\text{logit}(P(S = 1)) = \beta_0 + \beta_1 X + \beta_2 Y$ , where $S$ represents binary selection, $X$ is the exposure, and $Y$ is the outcome. The number of parameters therefore equals 3.   |
| level         | Value from 0-1 representing the full range of the confidence interval. Default is 0.95.   |

### Details

Values for the regression coefficients can be applied as fixed values or as single draws from a probability distribution (ex: `rnorm(1, mean = 2, sd = 1)`). The latter has the advantage of allowing the researcher to capture the uncertainty in the bias parameter estimates. To incorporate this uncertainty in the estimate and confidence interval, this function should be run in loop across bootstrap samples of the dataframe for analysis. The estimate and confidence interval would then be obtained from the median and quantiles of the distribution of odds ratio estimates.

**Value**

A list where the first item is the odds ratio estimate of the effect of the exposure on the outcome and the second item is the confidence interval as the vector: (lower bound, upper bound).

**Examples**

```
df <- data_observed(
  data = df_uc_sel,
  exposure = "X",
  outcome = "Y",
  confounders = c("C1", "C2", "C3")
)
adjust_uc_sel(
  df,
  u_model_coefs = c(-0.19, 0.61, 0.72, -0.09, 0.10, -0.15),
  s_model_coefs = c(-0.01, 0.92, 0.94)
)
```

---

data_observed	<i>Represent observed causal data</i>
---------------	---------------------------------------

---

**Description**

data\_observed combines the observed dataframe with specific identification of the columns corresponding to the exposure, outcome, and confounders. It is an essential input of all adjust functions.

**Usage**

```
data_observed(data, exposure, outcome, confounders = NULL)
```

**Arguments**

data	Dataframe for bias analysis.
exposure	String name of the column in data corresponding to the exposure variable.
outcome	String name of the column in data corresponding to the outcome variable.
confounders	String name(s) of the column(s) in data corresponding to the confounding variable(s).

**Examples**

```
df <- data_observed(
  data = df_sel,
  exposure = "X",
  outcome = "Y",
  confounders = c("C1", "C2", "C3")
)
```

---

data_validation	<i>Represent validation causal data</i>
-----------------	---

---

## Description

data\_validation combines the validation dataframe with specific identification of the appropriate columns for bias adjustment, including: true exposure, true outcome, confounders, misclassified exposure, misclassified outcome, and selection. The purpose of validation data is to use an external data source to transport the necessary causal relationships that are missing in the observed data.

## Usage

```
data_validation(  
  data,  
  true_exposure,  
  true_outcome,  
  confounders = NULL,  
  misclassified_exposure = NULL,  
  misclassified_outcome = NULL,  
  selection = NULL  
)
```

## Arguments

data	Dataframe of validation data
true_exposure	String name of the column in data corresponding to the true exposure.
true_outcome	String name of the column in data corresponding to the true outcome.
confounders	String name(s) of the column(s) in data corresponding to the confounding variable(s).
misclassified_exposure	String name of the column in data corresponding to the misclassified exposure.
misclassified_outcome	String name of the column in data corresponding to the misclassified outcome.
selection	String name of the column in data corresponding to the selection indicator.

## Examples

```
df <- data_validation(  
  data = df_sel_source,  
  true_exposure = "X",  
  true_outcome = "Y",  
  confounders = c("C1", "C2", "C3"),  
  selection = "S"  
)
```



---

df_em	<i>Simulated data with exposure misclassification</i>
-------	---

---

**Description**

Data containing one source of bias, three known confounders, and 100,000 observations. This data is obtained from df\_emc\_source by removing the column *X*. The resulting data corresponds to what a researcher would see in the real-world: a misclassified exposure, *Xstar*, and no data on the true exposure. As seen in df\_emc\_source, the true, unbiased exposure-outcome odds ratio = 2.

**Usage**

df\_em

**Format**

A dataframe with 100,000 rows and 5 columns:

**Xstar** misclassified exposure, 1 = present and 0 = absent

**Y** outcome, 1 = present and 0 = absent

**C1** 1st confounder, 1 = present and 0 = absent

**C2** 2nd confounder, 1 = present and 0 = absent

**C3** 3rd confounder, 1 = present and 0 = absent

---

df_em_om	<i>Simulated data with exposure misclassification and outcome misclassification</i>
----------	---

---

**Description**

Data containing two sources of bias, three known confounders, and 100,000 observations. This data is obtained from df\_emc\_omc\_source by removing the columns *X* and *Y*. The resulting data corresponds to what a researcher would see in the real-world: a misclassified exposure, *Xstar*, and a misclassified outcome, *Ystar*. As seen in df\_em\_om\_source, the true, unbiased exposure-outcome odds ratio = 2.

**Usage**

df\_em\_om

**Format**

A dataframe with 100,000 rows and 5 columns:

**Xstar** misclassified exposure, 1 = present and 0 = absent

**Ystar** misclassified outcome, 1 = present and 0 = absent

**C1** 1st confounder, 1 = present and 0 = absent

**C2** 2nd confounder, 1 = present and 0 = absent

**C3** 3rd confounder, 1 = present and 0 = absent

---

df_em_om_source	<i>Data source for df_em_om</i>
-----------------	---------------------------------

---

**Description**

Data with complete information on the two sources of bias, three known confounders, and 100,000 observations. This data is used to derive df\_em\_om and can be used to obtain bias parameters for purposes of validating the simultaneous multi-bias adjustment method with df\_em\_om. With this source data, the fitted regression  $\text{logit}(P(Y = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 C1 + \alpha_3 C2 + \alpha_4 C3$  shows that the true, unbiased exposure-outcome odds ratio = 2.

**Usage**

df\_em\_om\_source

**Format**

A dataframe with 100,000 rows and 7 columns:

**X** true exposure, 1 = present and 0 = absent

**Y** outcome, 1 = present and 0 = absent

**C1** 1st confounder, 1 = present and 0 = absent

**C2** 2nd confounder, 1 = present and 0 = absent

**C3** 3rd confounder, 1 = present and 0 = absent

**Xstar** misclassified exposure, 1 = present and 0 = absent

**Ystar** misclassified outcome, 1 = present and 0 = absent

df\_em\_sel

*Simulated data with exposure misclassification and selection bias***Description**

Data containing two sources of bias, three known confounders, and 100,000 observations. This data is obtained by sampling with replacement with probability =  $S$  from `df_em_sel_source` then removing the columns  $X$  and  $S$ . The resulting data corresponds to what a researcher would see in the real-world: a misclassified exposure,  $X_{star}$ , and missing data for those not selected into the study ( $S=0$ ). As seen in `df_em_sel_source`, the true, unbiased exposure-outcome odds ratio = 2.

**Usage**

df\_em\_sel

**Format**

A dataframe with 100,000 rows and 5 columns:

**Xstar** misclassified exposure, 1 = present and 0 = absent

**Y** outcome, 1 = present and 0 = absent

**C1** 1st confounder, 1 = present and 0 = absent

**C2** 2nd confounder, 1 = present and 0 = absent

**C3** 3rd confounder, 1 = present and 0 = absent

df\_em\_sel\_source

*Data source for df\_em\_sel***Description**

Data with complete information on the two sources of bias, three known confounders, and 100,000 observations. This data is used to derive `df_em_sel` and can be used to obtain bias parameters for purposes of validating the simultaneous multi-bias adjustment method with `df_em_sel`. With this source data, the fitted regression  $\text{logit}(P(Y = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 C1 + \alpha_3 C2 + \alpha_4 C3$  shows that the true, unbiased exposure-outcome odds ratio = 2.

**Usage**

df\_em\_sel\_source

**Format**

A dataframe with 100,000 rows and 7 columns:

**X** true exposure, 1 = present and 0 = absent

**Y** outcome, 1 = present and 0 = absent

**C1** 1st confounder, 1 = present and 0 = absent

**C2** 2nd confounder, 1 = present and 0 = absent

**C3** 3rd confounder, 1 = present and 0 = absent

**Xstar** misclassified exposure, 1 = present and 0 = absent

**S** selection, 1 = selected into the study and 0 = not selected into the study

---

df_em_source	<i>Data source for df_em</i>
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---

**Description**

Data with complete information on one sources of bias, three known confounders, and 100,000 observations. This data is used to derive df\_em and can be used to obtain bias parameters for purposes of validating the simultaneous multi-bias adjustment method with df\_em. With this source data, the fitted regression  $\text{logit}(P(Y = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 C1 + \alpha_3 C2 + \alpha_4 C3$  shows that the true, unbiased exposure-outcome odds ratio = 2.

**Usage**

df\_em\_source

**Format**

A dataframe with 100,000 rows and 6 columns:

**X** exposure, 1 = present and 0 = absent

**Y** true outcome, 1 = present and 0 = absent

**C1** 1st confounder, 1 = present and 0 = absent

**C2** 2nd confounder, 1 = present and 0 = absent

**C3** 3rd confounder, 1 = present and 0 = absent

**Xstar** misclassified exposure, 1 = present and 0 = absent

---

`df_om`*Simulated data with outcome misclassification*

---

**Description**

Data containing one source of bias, three known confounders, and 100,000 observations. This data is obtained from `df_om_source` by removing the column `Y`. The resulting data corresponds to what a researcher would see in the real-world: a misclassified outcome, *Ystar*, and no data on the true outcome. As seen in `df_om_source`, the true, unbiased exposure-outcome odds ratio = 2.

**Usage**`df_om`**Format**

A dataframe with 100,000 rows and 5 columns:

**X** exposure, 1 = present and 0 = absent

**Ystar** misclassified outcome, 1 = present and 0 = absent

**C1** 1st confounder, 1 = present and 0 = absent

**C2** 2nd confounder, 1 = present and 0 = absent

**C3** 3rd confounder, 1 = present and 0 = absent

---

`df_om_sel`*Simulated data with outcome misclassification and selection bias*

---

**Description**

Data containing two sources of bias, a known confounder, and 100,000 observations. This data is obtained by sampling with replacement with probability =  $S$  from `df_om_sel_source` then removing the columns `Y` and `S`. The resulting data corresponds to what a researcher would see in the real-world: a misclassified outcome, *Ystar*, and missing data for those not selected into the study ( $S=0$ ). As seen in `df_om_sel_source`, the true, unbiased exposure-outcome odds ratio = 2.

**Usage**`df_om_sel`

**Format**

A dataframe with 100,000 rows and 5 columns:

**X** exposure, 1 = present and 0 = absent

**Ystar** misclassified outcome, 1 = present and 0 = absent

**C1** 1st confounder, 1 = present and 0 = absent

**C2** 2nd confounder, 1 = present and 0 = absent

**C3** 3rd confounder, 1 = present and 0 = absent

---

df_om_sel_source	<i>Data source for df_om_sel</i>
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---

**Description**

Data with complete information on the two sources of bias, a known confounder, and 100,000 observations. This data is used to derive df\_om\_sel and can be used to obtain bias parameters for purposes of validating the simultaneous multi-bias adjustment method with df\_om\_sel. With this source data, the fitted regression  $\text{logit}(P(Y = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 C1 + \alpha_3 C2 + \alpha_4 C3$  shows that the true, unbiased exposure-outcome odds ratio = 2.

**Usage**

df\_om\_sel\_source

**Format**

A dataframe with 100,000 rows and 7 columns:

**X** exposure, 1 = present and 0 = absent

**Y** true outcome, 1 = present and 0 = absent

**C1** 1st confounder, 1 = present and 0 = absent

**C2** 2nd confounder, 1 = present and 0 = absent

**C3** 3rd confounder, 1 = present and 0 = absent

**Ystar** misclassified outcome, 1 = present and 0 = absent

**S** selection, 1 = selected into the study and 0 = not selected into the study

---

df_om_source	<i>Data source for df_om</i>
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---

### Description

Data with complete information on one sources of bias, three known confounders, and 100,000 observations. This data is used to derive df\_om and can be used to obtain bias parameters for purposes of validating the simultaneous multi-bias adjustment method with df\_om. With this source data, the fitted regression  $\text{logit}(P(Y = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 C1 + \alpha_3 C2 + \alpha_4 C3$  shows that the true, unbiased exposure-outcome odds ratio = 2.

### Usage

df\_om\_source

### Format

A dataframe with 100,000 rows and 6 columns:

**X** exposure, 1 = present and 0 = absent

**Y** true outcome, 1 = present and 0 = absent

**C1** 1st confounder, 1 = present and 0 = absent

**C2** 2nd confounder, 1 = present and 0 = absent

**C3** 3rd confounder, 1 = present and 0 = absent

**Ystar** misclassified outcome, 1 = present and 0 = absent

---

df_sel	<i>Simulated data with selection bias</i>
--------	---

---

### Description

Data containing one source of bias, three known confounders, and 100,000 observations. This data is obtained by sampling with replacement with probability =  $S$  from df\_sel\_source then removing the  $S$  column. The resulting data corresponds to what a researcher would see in the real-world: missing data for those not selected into the study ( $S=0$ ). As seen in df\_sel\_source, the true, unbiased exposure-outcome odds ratio = 2.

### Usage

df\_sel

**Format**

A dataframe with 100,000 rows and 5 columns:

**X** exposure, 1 = present and 0 = absent

**Y** outcome, 1 = present and 0 = absent

**C1** 1st confounder, 1 = present and 0 = absent

**C2** 2nd confounder, 1 = present and 0 = absent

**C3** 3rd confounder, 1 = present and 0 = absent

---

df_sel_source	<i>Data source for df_sel</i>
---------------	-------------------------------

---

**Description**

Data with complete information on study selection, three known confounders, and 100,000 observations. This data is used to derive `df_sel` and can be used to obtain bias parameters for purposes of validating the simultaneous multi-bias adjustment method with `df_sel`. With this source data, the fitted regression  $\text{logit}(P(Y = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 C1 + \alpha_3 C2 + \alpha_4 C3$  shows that the true, unbiased exposure-outcome odds ratio = 2.

**Usage**

`df_sel_source`

**Format**

A dataframe with 100,000 rows and 6 columns:

**X** true exposure, 1 = present and 0 = absent

**Y** outcome, 1 = present and 0 = absent

**C1** 1st confounder, 1 = present and 0 = absent

**C2** 2nd confounder, 1 = present and 0 = absent

**C3** 3rd confounder, 1 = present and 0 = absent

**S** selection, 1 = selected into the study and 0 = not selected into the study



df\_uc

*Simulated data with uncontrolled confounding***Description**

Data containing one source of bias, three known confounders, and 100,000 observations. This data is obtained from `df_uc_source` by removing the column `U`. The resulting data corresponds to what a researcher would see in the real-world: information on known confounders (`C1`, `C2`, and `C3`), but not for confounder `U`. As seen in `df_uc_source`, the true, unbiased exposure-outcome effect estimate = 2.

**Usage**

df\_uc

**Format**

A dataframe with 100,000 rows and 7 columns:

**X\_bi** binary exposure, 1 = present and 0 = absent

**X\_cont** continuous exposure

**Y\_bi** binary outcome corresponding to exposure `X_bi`, 1 = present and 0 = absent

**Y\_cont** continuous outcome corresponding to exposure `X_cont`

**C1** 1st confounder, 1 = present and 0 = absent

**C2** 2nd confounder, 1 = present and 0 = absent

**C3** 3rd confounder, 1 = present and 0 = absent

df\_uc\_em

*Simulated data with uncontrolled confounding and exposure misclassification***Description**

Data containing two sources of bias, three known confounders, and 100,000 observations. This data is obtained from `df_uc_em_source` by removing the columns `X` and `U`. The resulting data corresponds to what a researcher would see in the real-world: a misclassified exposure, `Xstar`, and missing data on a confounder `U`. As seen in `df_uc_em_source`, the true, unbiased exposure-outcome odds ratio = 2.

**Usage**

df\_uc\_em

**Format**

A dataframe with 100,000 rows and 5 columns:

**Xstar** misclassified exposure, 1 = present and 0 = absent

**Y** outcome, 1 = present and 0 = absent

**C1** 1st confounder, 1 = present and 0 = absent

**C2** 2nd confounder, 1 = present and 0 = absent

**C3** 3rd confounder, 1 = present and 0 = absent

---

df_uc_em_sel	<i>Simulated data with uncontrolled confounding, exposure misclassification, and selection bias</i>
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---

**Description**

Data containing three sources of bias, three known confounders, and 100,000 observations. This data is obtained by sampling with replacement with probability =  $S$  from `df_uc_em_sel_source` then removing the columns  $X$ ,  $U$ , and  $S$ . The resulting data corresponds to what a researcher would see in the real-world: a misclassified exposure,  $Xstar$ ; missing data on a confounder  $U$ ; and missing data for those not selected into the study ( $S=0$ ). As seen in `df_uc_em_sel_source`, the true, unbiased exposure-outcome odds ratio = 2.

**Usage**

`df_uc_em_sel`

**Format**

A dataframe with 100,000 rows and 5 columns:

**Xstar** misclassified exposure, 1 = present and 0 = absent

**Y** outcome, 1 = present and 0 = absent

**C1** 1st confounder, 1 = present and 0 = absent

**C2** 2nd confounder, 1 = present and 0 = absent

**C3** 3rd confounder, 1 = present and 0 = absent

---

df\_uc\_em\_sel\_source      *Data source for df\_uc\_em\_sel*


---

**Description**

Data with complete information on the three sources of bias, three known confounders, and 100,000 observations. This data is used to derive df\_uc\_em\_sel and can be used to obtain bias parameters for purposes of validating the simultaneous multi-bias adjustment method with df\_uc\_em\_sel. With this source data, the fitted regression  $\text{logit}(P(Y = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 C1 + \alpha_3 C2 + \alpha_4 C3 + \alpha_5 U$  shows that the true, unbiased exposure-outcome odds ratio = 2.

**Usage**

df\_uc\_em\_sel\_source

**Format**

A dataframe with 100,000 rows and 8 columns:

**X** true exposure, 1 = present and 0 = absent

**Y** outcome, 1 = present and 0 = absent

**C1** 1st confounder, 1 = present and 0 = absent

**C2** 2nd confounder, 1 = present and 0 = absent

**C3** 3rd confounder, 1 = present and 0 = absent

**U** unmeasured confounder, 1 = present and 0 = absent

**Xstar** misclassified exposure, 1 = present and 0 = absent

**S** selection, 1 = selected into the study and 0 = not selected into the study

---

df\_uc\_em\_source      *Data source for df\_uc\_em*


---

**Description**

Data with complete information on the two sources of bias, a known confounder, and 100,000 observations. This data is used to derive df\_uc\_em and can be used to obtain bias parameters for purposes of validating the simultaneous multi-bias adjustment method with df\_uc\_em. With this source data, the fitted regression  $\text{logit}(P(Y = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 C1 + \alpha_3 U$  shows that the true, unbiased exposure-outcome odds ratio = 2.

**Usage**

df\_uc\_em\_source

**Format**

A dataframe with 100,000 rows and 7 columns:

**X** true exposure, 1 = present and 0 = absent

**Y** outcome, 1 = present and 0 = absent

**C1** 1st confounder, 1 = present and 0 = absent

**C2** 2nd confounder, 1 = present and 0 = absent

**C3** 3rd confounder, 1 = present and 0 = absent

**U** unmeasured confounder, 1 = present and 0 = absent

**Xstar** misclassified exposure, 1 = present and 0 = absent

---

df\_uc\_om

*Simulated data with uncontrolled confounding and outcome misclassification*

---

**Description**

Data containing two sources of bias, three known confounders, and 100,000 observations. This data is obtained from df\_uc\_om\_source by removing the columns *Y* and *U*. The resulting data corresponds to what a researcher would see in the real-world: a misclassified outcome, *Ystar*, and missing data on the binary confounder *U*. As seen in df\_uc\_omc\_source, the true, unbiased exposure-outcome odds ratio = 2.

**Usage**

df\_uc\_om

**Format**

A dataframe with 100,000 rows and 5 columns:

**X** exposure, 1 = present and 0 = absent

**Ystar** misclassified outcome, 1 = present and 0 = absent

**C1** 1st confounder, 1 = present and 0 = absent

**C2** 2nd confounder, 1 = present and 0 = absent

**C3** 3rd confounder, 1 = present and 0 = absent

---

df_uc_om_sel	<i>Simulated data with uncontrolled confounding, outcome misclassification, and selection bias</i>
--------------	--

---

### Description

Data containing three sources of bias, three known confounders, and 100,000 observations. This data is obtained by sampling with replacement with probability =  $S$  from `df_uc_om_sel_source` then removing the columns  $Y$ ,  $U$ , and  $S$ . The resulting data corresponds to what a researcher would see in the real-world: a misclassified outcome,  $Y_{star}$ ; missing data on a confounder  $U$ ; and missing data for those not selected into the study ( $S=0$ ). As seen in `df_uc_om_sel_source`, the true, unbiased exposure-outcome odds ratio = 2.

### Usage

```
df_uc_om_sel
```

### Format

A dataframe with 100,000 rows and 5 columns:

**X** exposure, 1 = present and 0 = absent

**Ystar** misclassified outcome, 1 = present and 0 = absent

**C1** 1st confounder, 1 = present and 0 = absent

**C2** 2nd confounder, 1 = present and 0 = absent

**C3** 3rd confounder, 1 = present and 0 = absent

---

df_uc_om_sel_source	<i>Data source for df_uc_om_sel</i>
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---

### Description

Data with complete information on the three sources of bias, three known confounders, and 100,000 observations. This data is used to derive `df_uc_om_sel` and can be used to obtain bias parameters for purposes of validating the simultaneous multi-bias adjustment method with `df_uc_om_sel`. With this source data, the fitted regression  $\text{logit}(P(Y = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 C1 + \alpha_3 C2 + \alpha_4 C3 + \alpha_5 U$  shows that the true, unbiased exposure-outcome odds ratio = 2.

### Usage

```
df_uc_om_sel_source
```

**Format**

A dataframe with 100,000 rows and 8 columns:

**X** exposure, 1 = present and 0 = absent

**Y** true outcome, 1 = present and 0 = absent

**C1** 1st confounder, 1 = present and 0 = absent

**C2** 2nd confounder, 1 = present and 0 = absent

**C3** 3rd confounder, 1 = present and 0 = absent

**U** unmeasured confounder, 1 = present and 0 = absent

**Ystar** misclassified outcome, 1 = present and 0 = absent

**S** selection, 1 = selected into the study and 0 = not selected into the study

---

df_uc_om_source	<i>Data source for df_uc_om</i>
-----------------	---------------------------------

---

**Description**

Data with complete information on the two sources of bias, three known confounders, and 100,000 observations. This data is used to derive df\_uc\_om and can be used to obtain bias parameters for purposes of validating the simultaneous multi-bias adjustment method with df\_uc\_om. With this source data, the fitted regression  $\text{logit}(P(Y = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 C1 + \alpha_3 U$  shows that the true, unbiased exposure-outcome odds ratio = 2.

**Usage**

df\_uc\_om\_source

**Format**

A dataframe with 100,000 rows and 7 columns:

**X** exposure, 1 = present and 0 = absent

**Y** outcome, 1 = present and 0 = absent

**C1** 1st confounder, 1 = present and 0 = absent

**C2** 2nd confounder, 1 = present and 0 = absent

**C3** 3rd confounder, 1 = present and 0 = absent

**U** unmeasured confounder, 1 = present and 0 = absent

**Ystar** misclassified outcome, 1 = present and 0 = absent

df\_uc\_sel

*Simulated data with uncontrolled confounding and selection bias***Description**

Data containing two sources of bias, three known confounders, and 100,000 observations. This data is obtained by sampling with replacement with probability =  $S$  from `df_uc_sel_source` then removing the columns  $U$  and  $S$ . The resulting data corresponds to what a researcher would see in the real-world: missing data on confounder  $U$ ; and missing data for those not selected into the study ( $S=0$ ). As seen in `df_uc_sel_source`, the true, unbiased exposure-outcome odds ratio = 2.

**Usage**

df\_uc\_sel

**Format**

A dataframe with 100,000 rows and 5 columns:

**X** exposure, 1 = present and 0 = absent

**Y** outcome, 1 = present and 0 = absent

**C1** 1st confounder, 1 = present and 0 = absent

**C2** 2nd confounder, 1 = present and 0 = absent

**C3** 3rd confounder, 1 = present and 0 = absent

df\_uc\_sel\_source

*Data source for df\_uc\_sel***Description**

Data with complete information on the two sources of bias, a known confounder, and 100,000 observations. This data is used to derive `df_uc_sel` and can be used to obtain bias parameters for purposes of validating the simultaneous multi-bias adjustment method with `df_uc_sel`. With this source data, the fitted regression  $\text{logit}(P(Y = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 C1 + \alpha_3 C2 + \alpha_4 C3 + \alpha_5 U$  shows that the true, unbiased exposure-outcome odds ratio = 2.

**Usage**

df\_uc\_sel\_source

**Format**

A dataframe with 100,000 rows and 7 columns:

**X** true exposure, 1 = present and 0 = absent

**Y** outcome, 1 = present and 0 = absent

**C1** 1st confounder, 1 = present and 0 = absent

**C2** 2nd confounder, 1 = present and 0 = absent

**C3** 3rd confounder, 1 = present and 0 = absent

**U** unmeasured confounder, 1 = present and 0 = absent

**S** selection, 1 = selected into the study and 0 = not selected into the study

---

df\_uc\_source

*Data source for df\_uc*

---

**Description**

Data with complete information on one source of bias, three known confounders, and 100,000 observations. This data is used to derive df\_uc and can be used to obtain bias parameters for purposes of validating the simultaneous multi-bias adjustment method with df\_uc. With this source data, the fitted regression  $\text{logit}(P(Y = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 C1 + \alpha_3 C2 + \alpha_4 C3 + \alpha_5 U$  shows that the true, unbiased exposure-outcome effect estimate = 2 when:

1.  $g = \text{logit}$ ,  $Y = Y_{bi}$ , and  $X = X_{bi}$  or
2.  $g = \text{identity}$ ,  $Y = Y_{cont}$ ,  $X = X_{cont}$ .

**Usage**

df\_uc\_source

**Format**

A dataframe with 100,000 rows and 8 columns:

**X\_bi** binary exposure, 1 = present and 0 = absent

**X\_cont** continuous exposure

**Y\_bi** binary outcome corresponding to exposure  $X_{bi}$ , 1 = present and 0 = absent

**Y\_cont** continuous outcome corresponding to exposure  $X_{cont}$

**C1** 1st confounder, 1 = present and 0 = absent

**C2** 2nd confounder, 1 = present and 0 = absent

**C3** 3rd confounder, 1 = present and 0 = absent

**U** uncontrolled confounder, 1 = present and 0 = absent



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evans

*Evans County dataset*

---

**Description**

Data from a cohort study in which white males in Evans County were followed for 7 years, with coronary heart disease as the outcome of interest.

**Usage**

evans

**Format**

A dataframe with 609 rows and 9 columns:

**ID** subject identification

**CHD** outcome variable; 1 = coronary heart disease

**AGE** age (in years)

**CHL** cholesterol, mg/dl

**SMK** 1 = subject has ever smoked

**ECG** 1 = presence of electrocardiogram abnormality

**DBP** diastolic blood pressure, mmHg

**SBP** systolic blood pressure, mmHg

**HPT** 1 = SBP greater than or equal to 160 or DBP greater than or equal to 95

**Source**

<http://web1.sph.emory.edu/dkleinb/logreg3.htm#data>

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