eAppendix 1: the SAS code for implementing the parametric bootstrap method.

data a;
  input a b y f;
cards;
1 1 1 225
1 1 0 166
1 0 1  6
1 0 0 12
0 1 1  8
0 1 0 18
0 0 1  3
0 0 0 20
;
proc print data=a noobs;
  title "Example data";
  footnote "a & b are exposure factors, y is outcome, and f is frequency";
proc freq data=a noprint;
  weight f;
  tables a*b*y/sparse out=b;
proc sort data=b;
  by a b y;
data c;
  set b end=end;
  retain hold n00 p00 n01 p01 n10 p10 n11 p11;
  by a b y;
  if first.b then hold=count;
  if last.b then do;
    n=hold+count;
    p=count/n;
  end;
  if a=0 and b=0 then do; n00=n; p00=p; end;
  if a=1 and b=0 then do; n10=n; p10=p; end;
  if a=0 and b=1 then do; n01=n; p01=p; end;
  if a=1 and b=1 then do; n11=n; p11=p; end;
  if end then output;
  keep n00 p00 n01 p01 n10 p10 n11 p11;
data d;
  set c;
  call streaminit(3);
  do j=1 to 1000;
    y00=rand("binomial",p00,n00);
    y01=rand("binomial",p01,n01);
    y10=rand("binomial",p10,n10);
    y11=rand("binomial",p11,n11);
    hold=y11/(n11-y11+.5)-y10/(n10-y10+.5)-y01/(n01-y01+.5)-y00/(n00-y00)/(y00+.5)+1;
    reri=hold*(n00-y00)/(y00+.5)+1;
    output;
  end;
proc univariate data=d noprint;
  var reri;
  output out=e pctlpre=p pctlpts=2.5,97.5;
proc print data=e noobs round;
When there are no additional covariates, the purpose of the continuity correction used in equation (3) is to ensure \( \exp(\hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3) \), \( \exp(\hat{\beta}_1) \), and \( \exp(\hat{\beta}_2) \) are bounded.

For example, we replace \( \exp(\hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3) = \frac{y_{11} n_{00} - y_{00}}{n_{11} - y_{11} \cdot y_{00}} \) by \( \frac{y_{11} n_{00} - y_{00}}{n_{11} - y_{11} + .5 \cdot y_{00} + .5} \) to ensure \( \exp(\hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3) \) is bounded. With additional covariates the simple relation \( \exp(\hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3) = \frac{y_{11} n_{00} - y_{00}}{n_{11} - y_{11} \cdot y_{00}} \) does not hold, however we can directly constrain \( \hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3 \) so that \( \exp(\hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3) \), \( \exp(\hat{\beta}_1) \), and \( \exp(\hat{\beta}_2) \) are bounded.

Given covariate \( Z=z \), we assume

\[
p_{ijz} = \frac{\exp(\beta_0 + x_1\beta_1 + x_2\beta_2 + x_1x_2\beta_3 + z\beta)}{1 + \exp(\beta_0 + x_1\beta_1 + x_2\beta_2 + x_1x_2\beta_3 + z\beta)},
\]

we fit the logistic regression model with constraint that the absolute values of \( \hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3 \) are below a threshold, and further compute RERI through equation (1), i.e.

\[
RERI = \exp(\hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3) - \exp(\hat{\beta}_1) - \exp(\hat{\beta}_2) + 1.
\]

For general consideration on fitting logistic regression models with constrained parameters, please see Tian and al (2008) \(^8\) for details.