

# eAppendix of “Conditional and Unconditional Infectiousness Effects in Vaccine Trials”

## Proofs of Results 1 and 2

To prove Results 1 and 2, it is enough to show that

$$E[Y_{i2}(a_{i1}, Y_{i1}(1))] = E[Y_{i2}(a_{i1}) | Y_{i1}(1) = 1, Y_{i1}(0) = 1] \times \Pr(Y_{i1} = 1 | A_{i1} = 1)$$

holds under Assumptions 1 and 2. Under these assumptions,  $E[Y_{i2}(a_{i1}, Y_{i1}(1))]$  can be expressed as follows:

$$\begin{aligned} E[Y_{i2}(a_{i1}, Y_{i1}(1))] &= \sum_{s=0}^1 \sum_{t=0}^1 E[Y_{i2}(a_{i1}, Y_{i1}(1)) | Y_{i1}(1) = s, Y_{i1}(0) = t] \Pr(Y_{i1}(1) = s, Y_{i1}(0) = t) \\ &= E[Y_{i2}(a_{i1}, Y_{i1}(1)) | Y_{i1}(1) = 1, Y_{i1}(0) = 1] \Pr(Y_{i1}(1) = 1, Y_{i1}(0) = 1) \\ &\quad + E[Y_{i2}(a_{i1}, Y_{i1}(1)) | Y_{i1}(1) = 0, Y_{i1}(0) = 1] \Pr(Y_{i1}(1) = 0, Y_{i1}(0) = 1) \\ &\quad + E[Y_{i2}(a_{i1}, Y_{i1}(1)) | Y_{i1}(1) = 0, Y_{i1}(0) = 0] \Pr(Y_{i1}(1) = 0, Y_{i1}(0) = 0) \\ &= E[Y_{i2}(a_{i1}, 1) | Y_{i1}(1) = 1, Y_{i1}(0) = 1] \Pr(Y_{i1}(1) = 1, Y_{i1}(0) = 1) \\ &\quad + E[Y_{i2}(a_{i1}, 0) | Y_{i1}(1) = 0, Y_{i1}(0) = 1] \Pr(Y_{i1}(1) = 0, Y_{i1}(0) = 1) \\ &\quad + E[Y_{i2}(a_{i1}, 0) | Y_{i1}(1) = 0, Y_{i1}(0) = 0] \Pr(Y_{i1}(1) = 0, Y_{i1}(0) = 0) \\ &= E[Y_{i2}(a_{i1}, 1) | Y_{i1}(1) = 1, Y_{i1}(0) = 1] \Pr(Y_{i1}(1) = 1), \end{aligned} \tag{A1}$$

where the second equation is by Assumption 2 and the fourth is by Assumptions 1 and 2. In the last equation,  $E[Y_{i2}(a_{i1}, 1) | Y_{i1}(1) = 1, Y_{i1}(0) = 1]$  can be expressed as:

$$\begin{aligned} E[Y_{i2}(a_{i1}, 1) | Y_{i1}(1) = 1, Y_{i1}(0) = 1] &= E[Y_{i2}(a_{i1}, Y_{i1}(a_{i1})) | Y_{i1}(1) = 1, Y_{i1}(0) = 1] \\ &= E[Y_{i2}(a_{i1}) | Y_{i1}(1) = 1, Y_{i1}(0) = 1], \end{aligned} \tag{A2}$$

and  $\Pr(Y_{i1}(1) = 1)$  can be expressed as:

$$\Pr(Y_{i1}(1) = 1) = \Pr(Y_{i1}(1) = 1 | A_{i1} = 1) = \Pr(Y_{i1} = 1 | A_{i1} = 1) \tag{A3}$$

by random assignment to person 1 and the consistency assumption. Substituting (A2) and (A3) into (A1) completes the proof.

## Outlines of Methods for the Inference of the Conditional Infectiousness Effect

### *Marginal Structural Model*

To yield a CIE estimate by the marginal structural model under Assumption 2 and the assumption that  $Y_{i2}(a_{i1})$  is independent of  $A_{i1}$  conditional on  $Y_{i1}$  and  $C_i$ , we need only data for households with  $Y_{i1} = 1$ . The analysis can be conducted using a weighted regression model of  $A_{i1}$  on  $Y_{i2}$  with the weights  $w_i = 1$  for households with  $A_{i1} = 1$  and  $w_i = \Pr(A_{i1} = 1 \mid Y_{i1} = 1, C_i) / \Pr(A_{i1} = 0 \mid Y_{i1} = 1, C_i)$  for households with  $A_{i1} = 0$ .<sup>7</sup> The following is an SAS code, which was applied to the data in Table. Note that the data file “IPW” contains only data for households with  $Y_{i1} = 1$  in the original data file.

```
/* Estimation of Predicted Values */
proc logistic data=IPW descending;
  model A1=X;
  output out=PRED p=P;
run;
/* Calculation of the Weights */
data CIE;
  set PRED;
  if A1=1 then WEIGHT=1; else WEIGHT=P/(1-P);
run;
/* Weighted Analysis */
proc genmod data=CIE;
  class i;
  model Y2=A1/dist=poisson link=log;
  weight WEIGHT;
  repeated sub=i/type=ind;
  estimate 'beta' A1 1/exp;
run;
```

### *Bounds*

Under Assumption 2,  $E_{11}(a_{i1}) \equiv E[Y_{i2}(a_{i1}) \mid Y_{i1}(1) = 1, Y_{i1}(0) = 1]$  can be expressed as:

$$\begin{aligned} E[Y_{i2}(a_{i1}) \mid Y_{i1}(1) = 1, Y_{i1}(0) = 1] &= E[Y_{i2}(a_{i1}) \mid Y_{i1}(1) = 1] \\ &= E[Y_{i2}(a_{i1}) \mid A_{i1} = 1, Y_{i1} = 1]. \end{aligned}$$

For  $a_{i1} = 1$ ,

$$E[Y_{i2}(1) \mid Y_{i1}(1) = 1, Y_{i1}(0) = 1] = E[Y_{i2} \mid A_{i1} = 1, Y_{i1} = 1]$$

by the consistency assumption, and for  $a_{i1} = 0$ ,

$$E[Y_{i2}(0) | A_{i1} = 1, Y_{i1} = 1] \leq \frac{\Pr(Y_{i1} = 1 | A_{i1} = 0)}{\Pr(Y_{i1} = 1 | A_{i1} = 1)} E[Y_{i2} | A_{i1} = 0, Y_{i1} = 1],$$

because under Assumption 2,

$$\begin{aligned} E[Y_{i2} | A_{i1} = 0, Y_{i1} = 1] &= E[Y_{i2}(0) | A_{i1} = 0, Y_{i1} = 1] \\ &= E[Y_{i2}(0) | Y_{i1}(0) = 1] \\ &= E[Y_{i2}(0) | Y_{i1}(1) = 0, Y_{i1}(0) = 1] \Pr(Y_{i1}(1) = 0 | Y_{i1}(0) = 1) \\ &\quad + E[Y_{i2}(0) | Y_{i1}(1) = 1, Y_{i1}(0) = 1] \Pr(Y_{i1}(1) = 1 | Y_{i1}(0) = 1) \\ &\geq E[Y_{i2}(0) | Y_{i1}(1) = 1, Y_{i1}(0) = 1] \Pr(Y_{i1}(1) = 1 | Y_{i1}(0) = 1) \\ &= \frac{\Pr(Y_{i1}(1) = 1)}{\Pr(Y_{i1}(0) = 1)} E[Y_{i2}(0) | Y_{i1}(1) = 1] \\ &= \frac{\Pr(Y_{i1} = 1 | A_{i1} = 1)}{\Pr(Y_{i1} = 1 | A_{i1} = 0)} E[Y_{i2}(0) | A_{i1} = 1, Y_{i1} = 1]. \end{aligned}$$

Therefore, under Assumption 1, the lower bound for  $\text{CIE}_r \equiv E_{11}(1) / E_{11}(0)$  becomes

$$\begin{aligned} \text{CIE}_r &\geq \frac{E[Y_{i2} | A_{i1} = 1, Y_{i1} = 1]}{\frac{\Pr(Y_{i1} = 1 | A_{i1} = 0)}{\Pr(Y_{i1} = 1 | A_{i1} = 1)} E[Y_{i2} | A_{i1} = 0, Y_{i1} = 1]} \\ &= \frac{E[Y_{i2} | A_{i1} = 1, Y_{i1} = 1] \Pr(Y_{i1} = 1 | A_{i1} = 1) + E[Y_{i2} | A_{i1} = 1, Y_{i1} = 0] \Pr(Y_{i1} = 0 | A_{i1} = 1)}{E[Y_{i2} | A_{i1} = 0, Y_{i1} = 1] \Pr(Y_{i1} = 1 | A_{i1} = 0) + E[Y_{i2} | A_{i1} = 0, Y_{i1} = 0] \Pr(Y_{i1} = 0 | A_{i1} = 0)} \\ &= \frac{E[Y_{i2} | A_{i1} = 1]}{E[Y_{i2} | A_{i1} = 0]}. \end{aligned}$$

Under the assumption that  $E[Y_{i2}(0) | A_{i1} = 1, Y_{i1} = 1] \geq E[Y_{i2}(0) | A_{i1} = 0, Y_{i1} = 1]$ ,

$$\text{CIE}_r \leq \frac{E[Y_{i2} | A_{i1} = 1, Y_{i1} = 1]}{E[Y_{i2}(0) | A_{i1} = 0, Y_{i1} = 1]} = \frac{E[Y_{i2} | A_{i1} = 1, Y_{i1} = 1]}{E[Y_{i2} | A_{i1} = 0, Y_{i1} = 1]}.$$