

# 1 A Framework For Counterfactuals And Causal Inference

- (A-1) Two potential states, “untreated” and “treated,” with corresponding potential outcomes given by the variables  $(y_0, y_1)$ ,  $y_0, y_1 \in \mathfrak{R}$ . Extension to more than two potential outcomes is straightforward.
- (A-2) No market or social interactions among agents in the hypothetical world.
- (A-3) A static model.

A causal function for each state,

$$y_0 = g_0(x)$$

$$y_1 = g_1(x).$$

Letting  $\mathcal{D}_i$  be the domain of function  $g_i$ ,

$$g_0 : \mathcal{D}_0 \mapsto \mathfrak{R}, g_1 : \mathcal{D}_1 \mapsto \mathfrak{R} \text{ and } \mathcal{D}_i \subseteq \mathfrak{R}^J.$$

Let  $(\Omega, \mathcal{A}, P)$  denote a probability space. The random variables for the potential outcomes are  $(Y_0(\omega), Y_1(\omega))$   $X(\omega)$  produces the random variable  $Y(\omega)$ ,

$$(2-1a) \quad Y_0(\omega) = g_0(X(\omega))$$

$$(2-1b) \quad Y_1(\omega) = g_1(X(\omega))$$

$g_0, g_1$  functions are playing two roles in our analysis.

They are describing not only how the random vector  $X(\omega)$  is functionally related to the random variables  $Y_0(\omega), Y_1(\omega)$ , but also are specifying what values the outcomes would have taken had the causes  $X(\omega)$  taken alternative values.

A causal relationship is only well defined if a theory relating causes to outcomes is articulated and a mechanism generating