# Notes for Paper on Mis-measured, Binary, Endogenous Regressors

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# 1 Model and Notation

Fill in material from earlier notes so we have everything in one document!

$$p_{jk}^* = P(T^* = t, Z = k)$$
 $p_{jk} = P(T = t, Z = k)$ 
 $p_k^* = P(T^* = 1|Z = k)$ 
 $p_k = P(T = 1|Z = k)$ 
 $q = P(Z = 1)$ 

Thus,

$$\begin{split} p_{00}^* &= P(T^* = 0|Z = 0)P(Z = 0) = (1 - p_0^*)(1 - q) \\ &= \left(\frac{1 - p_0 - \alpha_1}{1 - \alpha_0 - \alpha_1}\right)(1 - q) \\ p_{10}^* &= P(T^* = 1|Z = 0)P(Z = 0) = p_0^*(1 - q) \\ &= \left(\frac{p_0 - \alpha_0}{1 - \alpha_0 - \alpha_1}\right)(1 - q) \\ p_{01}^* &= P(T^* = 0|Z = 1)P(Z = 1) = (1 - p_1^*)q \\ &= \left(\frac{1 - p_1 - \alpha_1}{1 - \alpha_0 - \alpha_1}\right)q \\ p_{11}^* &= P(T^* = 1|Z = 1)P(Z = 1) = p_1^*(1 - q) \\ &= \left(\frac{p_1 - \alpha_0}{1 - \alpha_0 - \alpha_1}\right)q \end{split}$$

## 2 CDF Conditions

#### 2.1 Notation

For  $t, Z \in \{0, 1\}$  define

$$F_{tk}^*(\tau) = P(Y \le \tau | T^* = t, Z = k)$$

$$F_{tk}(\tau) = P(Y \le \tau | T = t, Z = k)$$

$$F_k(\tau) = P(Y \le \tau | Z = k)$$

Note that the second two are observed for all t, k while the first is never observed since it depends on the unobserved RV  $T^*$ .

# **2.2** Bounds on $\alpha_0, \alpha_1$

Case I: No Assumptions on Z We begin by considering the bounds that we can derive for the mis-classification error rates without imposing any conditions on Z. In other words we use only the assumption that the measurement error is non-differential and the structure of the model, namely  $Y = \beta T^* + U$ . The bounds we obtain in this

way will be applicable even if the instrument is invalid. To begin, note that we can express the observable CDFs  $F_{tk}$  in terms of the unobservable CDFs  $F_{tk}^*$  according to

$$(1 - p_k)F_{0k}(\tau) = (1 - \alpha_0)(1 - p_k^*)F_{0k}^*(\tau) + \alpha_1 p_k^* F_{1k}^*(\tau)$$
$$p_k F_{1k}(\tau) = \alpha_0 (1 - p_k^*)F_{0k}^*(\tau) + (1 - \alpha_1)p_k^* F_{1k}^*(\tau)$$

for all k by Bayes' rule. Defining the shorthand

$$\widetilde{F}_{0k}(\tau) \equiv (1 - p_k) F_{0k}(\tau)$$

$$\widetilde{F}_{1k}(\tau) \equiv p_k F_{1k}(\tau)$$

this becomes

$$\widetilde{F}_{0k}(\tau) = (1 - \alpha_0)(1 - p_k^*)F_{0k}^*(\tau) + \alpha_1 p_k^* F_{1k}^*(\tau)$$
(2.1)

$$\widetilde{F}_{1k}(\tau) = \alpha_0 (1 - p_k^*) F_{0k}^*(\tau) + (1 - \alpha_1) p_k^* F_{1k}^*(\tau)$$
(2.2)

Now, solving Equation 2.1 for  $p_k^* F_{1k}^*(\tau)$  we have

$$p_k^* F_{1k}^*(\tau) = \frac{1}{\alpha_1} \left[ \tilde{F}_{0k}(\tau) - (1 - \alpha_0)(1 - p_k^*) F_{0k}^*(\tau) \right]$$

Substituting this into Equation 2.2,

$$\begin{split} \widetilde{F}_{1k}(\tau) &= \alpha_0 (1 - p_k^*) F_{0k}^*(\tau) + \frac{1 - \alpha_1}{\alpha_1} \left[ \widetilde{F}_{0k}(\tau) - (1 - \alpha_0) (1 - p_k^*) F_{0k}^*(\tau) \right] \\ &= \frac{1 - \alpha_1}{\alpha_1} \widetilde{F}_{0k}(\tau) + \left[ \alpha_0 - \frac{(1 - \alpha_1)(1 - \alpha_0)}{\alpha_1} \right] (1 - p_k^*) F_{0k}^*(\tau) \\ &= \frac{1 - \alpha_1}{\alpha_1} \widetilde{F}_{0k}(\tau) + \left[ \frac{\alpha_0 \alpha_1 - (1 - \alpha_1)(1 - \alpha_0)}{\alpha_1} \right] (1 - p_k^*) F_{0k}^*(\tau) \\ &= \frac{1 - \alpha_1}{\alpha_1} \widetilde{F}_{0k}(\tau) - \left[ \frac{(1 - \alpha_1)(1 - \alpha_0) - \alpha_0 \alpha_1}{\alpha_1} \right] (1 - p_k^*) F_{0k}^*(\tau) \\ &= \frac{1 - \alpha_1}{\alpha_1} \widetilde{F}_{0k}(\tau) - \left[ \frac{1 - \alpha_1 - \alpha_0}{\alpha_1} \right] \left( \frac{1 - p_k - \alpha_1}{1 - \alpha_0 - \alpha_1} \right) F_{0k}^*(\tau) \end{split}$$

and therefore

$$\tilde{F}_{1k}(\tau) = \frac{1 - \alpha_1}{\alpha_1} \tilde{F}_{0k}(\tau) - \frac{1 - p_k - \alpha_1}{\alpha_1} F_{0k}^*(\tau)$$
(2.3)

Equation 2.3 relates the observable  $\widetilde{F}_{1k}(\tau)$  to the mis-classification error rate  $\alpha_1$  and the unobservable CDF  $F_{0k}^*(\tau)$ . Since  $F_{0k}^*(\tau)$  is a CDF, however, it lies in the interval [0,1]. Accordingly, substituting 0 in place of  $F_{0k}^*(\tau)$  gives

$$\widetilde{F}_{1k}(\tau) \le \frac{1 - \alpha_1}{\alpha_1} \widetilde{F}_{0k}(\tau) \tag{2.4}$$

while substituting 1 gives

$$\widetilde{F}_{1k}(\tau) \ge \frac{1 - \alpha_1}{\alpha_1} \widetilde{F}_{0k}(\tau) - \frac{1 - p_k - \alpha_1}{\alpha_1} \tag{2.5}$$

Rearranging Equation 2.4

$$\alpha_{1}\widetilde{F}_{1k}(\tau) \leq (1 - \alpha_{1})\widetilde{F}_{0k}(\tau)$$

$$\alpha_{1}\widetilde{F}_{1k}(\tau) \leq \widetilde{F}_{0k}(\tau) - \alpha_{1}\widetilde{F}_{0k}(\tau)$$

$$\alpha_{1}\left[\widetilde{F}_{1k}(\tau) + \widetilde{F}_{1k}(\tau)\right] \leq \widetilde{F}_{0k}(\tau)$$

since  $\alpha_1 \in [0,1]$  and therefore

$$\alpha_1 \le \frac{\widetilde{F}_{0k}(\tau)}{\widetilde{F}_{1k}(\tau) + \widetilde{F}_{1k}(\tau)} \tag{2.6}$$

since  $\tilde{F}_{1k}(\tau) + \tilde{F}_{1k}(\tau) \geq 0$ . Proceeding similarly for Equation 2.5,

$$\alpha_{1}\widetilde{F}_{1k}(\tau) \geq (1 - \alpha_{1})\widetilde{F}_{0k}(\tau) - (1 - p_{k} - \alpha_{1})$$

$$\alpha_{1}\left[\widetilde{F}_{1k}(\tau) + \widetilde{F}_{0k}(\tau) - 1\right] \geq \widetilde{F}_{0k}(\tau) - (1 - p_{k})$$

$$-\alpha_{1}\left[1 - \widetilde{F}_{1k}(\tau) - \widetilde{F}_{0k}(\tau)\right] \geq -\left[1 - \widetilde{F}_{0k}(\tau) - p_{k}\right]$$

$$\alpha_{1}\left[1 - \widetilde{F}_{1k}(\tau) - \widetilde{F}_{0k}(\tau)\right] \leq 1 - \widetilde{F}_{0k}(\tau) - p_{k}$$

The bounds given by equations ??? and ??? relate the mis-classification error rate  $\alpha_1$  to observable quantities *only* and hold for all values of  $\tau$ .

## 2.3 Independent Instrument

Assume that  $Z \perp U$ . The model is  $Y = \beta T^* + U$  and

$$F_U(\tau) = P(U \le \tau) = P(Y - \beta T^* \le \tau)$$

but if Z is independent of U then it follows that

$$F_{U}(\tau) = F_{U|Z=k}(\tau) = P(U \le \tau | Z = k) = P(Y - \beta T^{*} \le \tau | Z = k)$$

$$= P(Y \le \tau | T^{*} = 0, Z = k)(1 - p_{k}^{*}) + P(Y \le \tau + \beta | T^{*} = 1, Z = k)p_{k}^{*}$$

$$= (1 - p_{k}^{*})F_{0k}^{*}(\tau) + p_{k}^{*}F_{1k}^{*}(\tau + \beta)$$

for all k by the Law of Total Probability. Similarly,

$$F_k(\tau) = (1 - p_k^*) F_{0k}^*(\tau) + p_k^* F_{1k}^*(\tau)$$

and rearranging

$$(1 - p_k^*)F_{0k}^*(\tau) = F_k(\tau) - p_k^*F_{1k}^*(\tau)$$

Substituting this expression into the equation for  $F_U(\tau)$  from above, we have

$$F_U(\tau) = F_k(\tau) + p_k^* \left[ F_{1k}^*(\tau + \beta) - F_{1k}^*(\tau) \right]$$

for all k and all  $\tau$ . Evaluating at two values k and  $\ell$  in the support of Z and equating

$$F_k(\tau) + p_k^* \left[ F_{1k}^*(\tau + \beta) - F_{1k}^*(\tau) \right] = F_\ell(\tau) + p_\ell^* \left[ F_{1\ell}^*(\tau + \beta) - F_{1\ell}^*(\tau) \right]$$

or equivalently

$$F_k(\tau) - F_\ell(\tau) = p_\ell^* \left[ F_{1\ell}^*(\tau + \beta) - F_{1\ell}^*(\tau) \right] - p_k^* \left[ F_{1k}^*(\tau + \beta) - F_{1k}^*(\tau) \right]$$
 (2.7)

for all  $\tau$ . Now we simply need to re-express all of the "star" quantities, namely  $p_k^*, p_\ell^*$  and  $F_{1k}^*, F_{1\ell}^*$  in terms of  $\alpha_0, \alpha_1$  and the *observable* probability distributions  $F_{1k}$  and  $F_{1\ell}$  and observable probabilities  $p_k, p_\ell$ . To do this, we use the fact that

$$F_{0k}(\tau) = \frac{1 - \alpha_0}{1 - p_k} (1 - p_k^*) F_{0k}^*(\tau) + \frac{\alpha_1}{1 - p_k} p_k^* F_{1k}^*(\tau)$$

$$F_{1k}(\tau) = \frac{\alpha_0}{p_k} (1 - p_k^*) F_{0k}^*(\tau) + \frac{1 - \alpha_1}{p_k} p_k^* F_{1k}^*(\tau)$$

for all k by Bayes' rule. Solving these equations,

$$p_k^* F_{1k}^*(\tau) = \frac{1 - \alpha_0}{1 - \alpha_0 - \alpha_1} p_k F_{1k}(\tau) - \frac{\alpha_0}{1 - \alpha_0 - \alpha_1} (1 - p_k) F_{0k}(\tau)$$

for all k. Combining this with Equation 2.7, we find that

$$(1 - \alpha_0 - \alpha_1) [F_k(\tau) - F_\ell(\tau)] = \alpha_0 \{ (1 - p_k) [F_{0k}(\tau + \beta) - F_{0k}(\tau)] - (1 - p_\ell) [F_{0\ell}(\tau + \beta) - F_{0\ell}(\tau)] \}$$
$$- (1 - \alpha_0) \{ p_k [F_{1k}(\tau + \beta) - F_{1k}(\tau)] - p_\ell [F_{1\ell}(\tau + \beta) - F_{1\ell}(\tau)] \}$$

Now, define

$$\Delta_{tk}^{\tau}(\beta) = F_{tk}(\tau + \beta) - F_{tk}(\tau) = E\left[\frac{\mathbf{1}\left\{T = t, Z = k\right\}}{p_{tk}} \left(\mathbf{1}\left\{Y \le \tau + \beta\right\} - \mathbf{1}\left\{Y \le \tau\right\}\right)\right]$$

and note that we can express  $F_k(\tau) - F_\ell(\tau)$  similarly as

$$F_k(\tau) - F_\ell(\tau) = E\left[\mathbf{1}\left\{Y \le \tau\right\} \left(\frac{\mathbf{1}\left\{Z = k\right\}}{q_k} - \frac{\mathbf{1}\left\{Z = \ell\right\}}{q_\ell}\right)\right]$$

Using this notation, we can write the preceding as

$$(1 - \alpha_0 - \alpha_1) \left[ F_k(\tau) - F_\ell(\tau) \right] = \alpha_0 \left[ (1 - p_k) \Delta_{0k}^{\tau}(\beta) - (1 - p_\ell) \Delta_{0\ell}^{\tau}(\beta) \right] - (1 - \alpha_0) \left[ p_k \Delta_{1k}^{\tau}(\beta) - p_\ell \Delta_{1\ell}^{\tau}(\beta) \right]$$

or in moment-condition form

$$E\left[ (1 - \alpha_0 - \alpha_1) \mathbf{1} \left\{ Y \le \tau \right\} \left( \frac{\mathbf{1} \left\{ Z = k \right\}}{q_k} - \frac{\mathbf{1} \left\{ Z = \ell \right\}}{q_\ell} \right) - (\mathbf{1} \left\{ Y \le \tau + \beta \right\} - \mathbf{1} \left\{ Y \le \tau \right\}) \right\}$$

$$\alpha_0 \left( (1 - p_k) \frac{\mathbf{1} \left\{ T = 0, Z = k \right\}}{p_{0k}} - (1 - p_\ell) \frac{\mathbf{1} \left\{ T = 0, Z = \ell \right\}}{p_{0\ell}} \right)$$

$$- (1 - \alpha_0) \left( p_k \frac{\mathbf{1} \left\{ T = 1, Z = k \right\}}{p_{1k}} - p_\ell \frac{\mathbf{1} \left\{ T = 1, Z = \ell \right\}}{p_{1\ell}} \right) \right\} = 0$$

Each value of  $\tau$  yields a moment condition.

## 3 Special Case: $\alpha_0 = 0$

In this case the expressions from above simplify to

$$(1 - \alpha_1) \left[ F_k(\tau) - F_{\ell}(\tau) \right] + \left\{ p_k \left[ F_{1k}(\tau + \beta) - F_{1k}(\tau) \right] - p_{\ell} \left[ F_{1\ell}(\tau + \beta) - F_{1\ell}(\tau) \right] \right\} = 0$$

for all  $\tau$ .