

Recitation Period 8: Understanding Fixed Effects

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March 6, 2025

This proof solves proposition 1 of Gibbons and coauthors' 2023 paper on the bias of Fixed Effects Estimator:

Proposition 1 (Bias of Fixed Effects under Heterogeneous Treatment Effects). *Consider the outcome model*

$$y_i = x_i \beta_{g(i)} + z_i' \gamma + \varepsilon_i, \quad (1)$$

where

- (i) $g(i) \in \{1, 2, \dots, G\}$ denotes the group to which observation i belongs;
- (ii) each group g may have its own slope β_g (i.e., treatment effect);
- (iii) z_i is a vector of additional covariates (including group dummies, time dummies, etc.);
- (iv) ε_i is a mean-zero error term satisfying standard OLS-type assumptions.

Define the average treatment effect (ATE) as

$$\beta_{\text{ATE}} = \sum_{g=1}^G \left(\frac{N_g}{N} \right) \beta_g, \quad \text{where } N_g = \sum_{i:g(i)=g} 1 \text{ and } N = \sum_{g=1}^G N_g.$$

Let \hat{b}_{FE} be the usual OLS estimator from a regression that includes group fixed effects but does not interact x_i with group dummies. Then if $\beta_g \neq \beta_{g'}$ for at least one pair (g, g') and the within-group variances of x_i (after partialing out z_i) differ, \hat{b}_{FE} is generally biased (and inconsistent) for β_{ATE} .

Proof of Proposition. Step 1: Residualize with respect to the other covariates z_i .

1. Let X, Z , and A collectively denote the full set of x_i, z_i , and group membership data. Define the “annihilator matrix”

$$M = I_N - Z(Z'Z)^{-1}Z',$$

which projects any N -vector orthogonally to the column space of Z .

2. For each observation i , define:

$$\tilde{y}_i = (M y)_i, \quad \tilde{x}_i = (M x)_i, \quad \tilde{\varepsilon}_i = (M \varepsilon)_i.$$

Then *by construction* $M z = 0$, so the model (1) becomes

$$\tilde{y}_i = \tilde{x}_i \beta_{g(i)} + \tilde{\varepsilon}_i,$$

because $M z_i = 0$ for each observation i .

Step 2: Write down the Fixed Effects (FE) estimator in residualized form.

The usual FE approach is equivalent to OLS regression of \tilde{y}_i on \tilde{x}_i , i.e.

$$\hat{b}_{\text{FE}} = \frac{\sum_{i=1}^N \tilde{x}_i \tilde{y}_i}{\sum_{i=1}^N \tilde{x}_i^2} = \frac{\tilde{x}' \tilde{y}}{\tilde{x}' \tilde{x}}. \quad (2)$$

Since $\tilde{y}_i = \tilde{x}_i \beta_{g(i)} + \tilde{\varepsilon}_i$, we have

$$\sum_{i=1}^N \tilde{x}_i \tilde{y}_i = \sum_{i=1}^N \tilde{x}_i^2 \beta_{g(i)} + \sum_{i=1}^N \tilde{x}_i \tilde{\varepsilon}_i.$$

Taking conditional expectation on (X, Z, A) , and assuming $\mathbb{E}[\tilde{x}_i \tilde{\varepsilon}_i \mid X, Z, A] = 0$ (the usual exogeneity assumption in OLS), we get

$$\mathbb{E}[\hat{b}_{\text{FE}} \mid X, Z, A] = \frac{\sum_{i=1}^N \tilde{x}_i^2 \beta_{g(i)}}{\sum_{i=1}^N \tilde{x}_i^2}. \quad (3)$$

Step 3: Express the sum in terms of group-specific components.

1. Partition the observations into G groups. Let $N_g = \sum_{i=1}^N \mathbf{1}_{\{g(i)=g\}}$ be the number of observations in group g . Set $\pi_g = N_g/N$.
2. In each group g , define the sample variance of \tilde{x}_i as

$$\widehat{\text{Var}}(\tilde{x}_i \mid g) = \frac{1}{N_g} \sum_{\substack{i=1 \\ g(i)=g}}^N \tilde{x}_i^2,$$

assuming that the group-mean of \tilde{x}_i has been subtracted out if necessary. Likewise, define

$$\widehat{\text{Var}}(\tilde{x}_i) = \frac{1}{N} \sum_{i=1}^N \tilde{x}_i^2.$$

Hence

$$\sum_{i=1}^N \tilde{x}_i^2 = N \times \widehat{\text{Var}}(\tilde{x}_i), \quad \sum_{\{i:g(i)=g\}} \tilde{x}_i^2 = N_g \times \widehat{\text{Var}}(\tilde{x}_i \mid g).$$

3. Rewrite the numerator of (3):

$$\sum_{i=1}^N \tilde{x}_i^2 \beta_{g(i)} = \sum_{g=1}^G \sum_{\{i:g(i)=g\}} \tilde{x}_i^2 \beta_g = \sum_{g=1}^G (N_g \widehat{\text{Var}}(\tilde{x}_i | g)) \beta_g.$$

Thus

$$\mathbb{E}[\hat{b}_{\text{FE}} | X, Z, A] = \frac{\sum_{g=1}^G N_g \widehat{\text{Var}}(\tilde{x}_i | g) \beta_g}{N \widehat{\text{Var}}(\tilde{x}_i)} = \sum_{g=1}^G \pi_g \beta_g \frac{\widehat{\text{Var}}(\tilde{x}_i | g)}{\widehat{\text{Var}}(\tilde{x}_i)}.$$

Step 4: Compare to β_{ATE} .

Recall that $\beta_{\text{ATE}} = \sum_{g=1}^G \pi_g \beta_g$. Subtracting, we obtain

$$\mathbb{E}[\hat{b}_{\text{FE}} | X, Z, A] - \beta_{\text{ATE}} = \sum_{g=1}^G (\pi_g \beta_g) \left[\frac{\widehat{\text{Var}}(\tilde{x}_i | g)}{\widehat{\text{Var}}(\tilde{x}_i)} - 1 \right].$$

Therefore, *unless* $\widehat{\text{Var}}(\tilde{x}_i | g)$ is the same across all groups g or $\{\beta_g\}$ is the same in every group, the above sum will *not* be zero. That is,

$$\mathbb{E}[\hat{b}_{\text{FE}} | X, Z, A] \neq \beta_{\text{ATE}}.$$

Step 5: Conclude bias and inconsistency.

1. We have shown that in expectation (conditional on X, Z, A), \hat{b}_{FE} does not recover β_{ATE} , hence there is a *bias*.

2. As $N \rightarrow \infty$, by standard laws of large numbers for sample variances, $\widehat{\text{Var}}(\tilde{x}_i | g)$ converges to the true within-group variance of \tilde{x}_i (provided that variance exists). Thus the ratio $\frac{\widehat{\text{Var}}(\tilde{x}_i | g)}{\widehat{\text{Var}}(\tilde{x}_i)}$ converges to the limit of the ratio of those variances. Consequently, if β_g differs by group and the ratio of within-group variances differs across groups, the limiting value of \hat{b}_{FE} is not β_{ATE} , showing *inconsistency* as well.

Thus,

$$\hat{b}_{\text{FE}} \xrightarrow{p} \sum_{g=1}^G \pi_g \beta_g \frac{\text{Var}(\tilde{x}_i | g)}{\text{Var}(\tilde{x}_i)} \neq \sum_{g=1}^G \pi_g \beta_g = \beta_{\text{ATE}},$$

whenever $\{\beta_g\}$ and $\text{Var}(\tilde{x}_i | g)$ vary across g . This completes the proof. \square