

Topic 3: Moving the Goalposts Approach

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Key points:

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Disclaimer: These notes are written by Sai Zhang ([email me](#) or check my [Github page](#)). The main references for this topic are [Armstrong et al. \(2020\)](#); [Armstrong and Kolesár \(2018\)](#), I thank Prof. Armstrong for his valuable advice.

3.1 Finite Sample Bias-Variance Tradeoffs

3.1.1 Setup

Consider the fixed design regression model

$$y_i = w_i \beta(z_i) + h(z_i) + \epsilon_i \quad (3.1)$$

where

- w_i, z_i are treated as **fixed**
- ϵ_i is **independent**, with $\mathbb{E}[\epsilon_i] = 0, \mathbb{E}[\epsilon_i^2] = \sigma_i^2$
- observation: $\left\{ \left(y_i, w_i, z_i' \right)' \right\}_{i=1}^n$

one example is the case where w_i is **binary**, then

$$\beta(z) = f(1, z) - f(0, z)$$

which is just the ATE conditional on z under the unconfoundedness assumption. This includes the RD design, where z_i is the running variable and w_i is the treatment assignment.

Now, consider for the weighted average treatment effect

$$L_\mu [\beta(\cdot)] = \int \beta(z) d\mu(z)$$

where $\int \mu(z) = 1$ is a **signed** measure (weight, allowing **negative** weights), construct a linear estimator

$$\hat{L}_a = \sum_{i=1}^n a_i y_i$$

where the estimation weights a_i can depend on $\{z_i, w_i, \sigma_i^2\}_{i=1}^n$, but **not** on y_i . Together, the bias of \hat{L}_a for $L_\mu [\beta(\cdot)]$, given the regression function $\beta(\cdot), h(\cdot)$, is

$$\mathbb{E}_{\beta(\cdot), h(\cdot)} [\hat{L}_a] - L_\mu [\beta(\cdot)] = \sum_{i=1}^n a_i [w_i \beta(z_i) + h(z_i)] - \int \beta(z) d\mu(z)$$

and its variance, given the regression function $\beta(\cdot)$, $h(\cdot)$, is just

$$\text{Var}_{\beta(\cdot), h(\cdot)} [\hat{L}_a] = \sum_{i=1}^n a_i^2 \sigma_i^2$$

To bound the bias, assume $h(\cdot)$ is known to belong in a class of functions \mathcal{H} , then two approaches can be adopted, for the regularity of $\beta(\cdot)$ and the choice of $\mu(\cdot)$:

- 1 arbitrary $\beta(\cdot)$, optimizing weights μ by *moving the goalposts*, s.t. $L_\mu [\beta(\cdot)]$ is easy to estimate (Crump et al., 2006; Imbens and Wager, 2019) which gives the worst-case bias

$$\inf_{\mu} \sup_{\beta(\cdot), h(\cdot)} \left| \sum_{i=1}^n a_i [w_i \beta(z_i) + h(z_i)] - \int \beta(z) d\mu(z) \right| \quad \text{s.t. } h(\cdot) \in \mathcal{H}, \int d\mu(z) = 1 \quad (3.2)$$

- 2 assume constant treatment effects, i.e., $\beta(z) = \beta, \forall z$, which means that $L_\mu [\beta(\cdot)] = \beta$ regardless of μ (Armstrong et al., 2020), and the worst-case bias is

$$\sup_{\beta, h(\cdot)} \left| \sum_{i=1}^n a_i [w_i \beta + h(z_i)] - \beta \right| \quad \text{s.t. } h(\cdot) \in \mathcal{H} \quad (3.3)$$

And, the two approaches can be linked as such:

- If $\sum_{i=1}^n a_i w_i = 1$, 3.2 and 3.3 are both equal to

$$\sup_{h(\cdot)} \left| \sum_{i=1}^n a_i h(z_i) \right| \quad \text{s.t. } h(\cdot) \in \mathcal{H} \quad (3.4)$$

- 3.2 automatically equals 3.4
- 3.3 is optimized (w.r.t. μ) by setting μ to place weight $a_i w_i$ on observation i , i.e., $\mu(\mathcal{Z}) = \sum_{i: z_i \in \mathcal{Z}} a_i w_i$, which implies $\sum_{i=1}^n a_i w_i \beta(z_i) - \int \beta(z) d\mu(z) = 0$, hence the equality.
- Otherwise, 3.2 and 3.3 are both infinite:
 - 3.3 can be made arbitrarily large by choosing large enough β
 - 3.2 can be made arbitrarily large by making $\beta(\cdot)$ constant (as in 3.3) and large enough

3.1.2 Moving-the-goalpost Approach

3.1.3 Constant-treatment-effect Approach

Armstrong et al. (2020) adopt this approach, focusing on the case where $h(\cdot)$ is a high dimensional linear function, and the penalty function is an l_p norm of the coefficients.

Basic setting: Homoskedastic Gaussian errors

First, consider

$$Y = w\beta + Z\gamma + \epsilon \quad (3.5)$$

where

- $\beta \in \mathbb{R}$ is the constant treatment effect to be estimated
- $\gamma \in \Gamma$ is the control coefficients, subject to the restriction (i.e., the function class \mathcal{H})

$$\Gamma = \Gamma(C) = \{\gamma \in \mathcal{G} : \text{Pen}(\gamma) \leq C\} \quad (3.6)$$

where $\text{Pen}(\cdot)$ is a seminorm¹ on some linear subspace \mathcal{G} of \mathbb{R}^k .

- $w = (w_1, \dots, w_n)' \in \mathbb{R}^n$ and $Z = (z'_1, \dots, z'_n)' \in \mathbb{R}^{n \times k}$ are defined as before
- $\epsilon \sim \mathcal{N}(0, \sigma^2 I_n)$ is assumed **normal and homoskedastic**, with σ^2 known

For estimation, the goal is to construct estimators and CIs for β :

- estimator $\hat{\beta}$: consider the worst-case performance over the parameter space $\mathbb{R} \times \Gamma$ under the **MSE** criterion

$$R_{MSE}(\hat{\beta}; \Gamma) = \sup_{\beta \in \mathbb{R}, \gamma \in \Gamma} \mathbb{E}_{\beta, \gamma} \left[(\hat{\beta} - \beta)^2 \right]$$

- for CIs, we have 2 requirements:

A **coverage**: A $100 \cdot (1 - \alpha)\%$ CI with half-length $\hat{\chi} = \hat{\chi}(Y, X)$ is an interval $\{\hat{\beta} \pm \hat{\chi}\}$ s.t.

$$\inf_{\beta \in \mathbb{R}, \gamma \in \Gamma} P_{\beta, \gamma}(\beta \in \{\hat{\beta} \pm \hat{\chi}\}) \geq 1 - \alpha$$

B **length**: the expected length of a CI $\mathbb{E}_{\beta, \gamma}[2\hat{\chi}]$ should be as short as possible

notice that length-optimized CIs are **not** necessarily centered at an MSE-centered $\hat{\beta}$.

Linear estimators and CIs

Again, consider estimators that are **linear** in the outcomes Y , $\hat{\beta} = a'Y$, where a is the n -vector weights. In the vector form, the worst-case bias (as 3.3) is

$$\overline{\text{bias}}_{\Gamma}(\hat{\beta}) = \sup_{\beta \in \mathbb{R}, \gamma \in \Gamma} a'(w\beta + Z\gamma) - \beta \quad (3.7)$$

and the variance, under the assumption of homoskedasticity, is

$$\text{Var}(\hat{\beta}) = \sigma^2 a'a$$

Then the MSE is

$$R_{MSE}(\hat{\beta}; \Gamma) = \sup_{\beta \in \mathbb{R}, \gamma \in \Gamma} \mathbb{E}_{\beta, \gamma} \left[(\hat{\beta} - \beta)^2 \right] = \overline{\text{bias}}_{\Gamma}(\hat{\beta})^2 + \text{Var}(\hat{\beta})$$

The t -statistic is

$$\frac{\hat{\beta} - \beta}{\sqrt{\text{Var}(\hat{\beta})}} \sim \mathcal{N}(b, 1), \quad |b| \leq \frac{\overline{\text{bias}}_{\Gamma}(\hat{\beta})}{\sqrt{\text{Var}(\hat{\beta})}}$$

and a two-sided CI can then be formed as

$$\hat{\beta} \pm \chi, \quad \text{where } \chi = \sqrt{\text{Var}(\hat{\beta})} \cdot \text{cv}_{\alpha} \left(\frac{\overline{\text{bias}}_{\Gamma}(\hat{\beta})}{\sqrt{\text{Var}(\hat{\beta})}} \right) \quad (3.8)$$

and the $\text{cv}_{\alpha}(B)$ denotes the $1 - \alpha$ quantile of a $|\mathcal{N}(B, 1)|$. This is a **fixed-length confidence interval (FLCI)**, with a fixed length of 2χ . It depends on X and σ^2 , but not on Y or $(\beta, \gamma)'$.

¹Seminorm satisfies **triangle inequality** $\text{Pen}(\gamma + \tilde{\gamma}) \leq \text{Pen}(\gamma) + \text{Pen}(\tilde{\gamma})$ and **homogeneity** $\text{Pen}(c\gamma) = |c| \text{Pen}(\gamma), \forall c$, but **NOT** necessarily positive definite ($\text{Pen}(\gamma) = 0$ does not imply $\gamma = 0$). Essentially, any convex set Γ that is symmetric satisfies this definition.

Optimal weights

We have two optimization goals

- minimizing MSE: $R_{MSE}(\hat{\beta}; \Gamma) = \overline{\text{bias}}_{\Gamma}(\hat{\beta})^2 + \text{Var}(\hat{\beta})$
- minimizing CI length: $\chi = \sqrt{\text{Var}(\hat{\beta})} \cdot \text{cv}_{\alpha} \left(\overline{\text{bias}}_{\Gamma}(\hat{\beta}) / \sqrt{\text{Var}(\hat{\beta})} \right)$

They both increasing in $\text{Var}(\hat{\beta})$ and $\overline{\text{bias}}_{\Gamma}(\hat{\beta})$, hence to find the optimal weights, it suffices to minimize variance subject to a bound B on worst-case bias, which can be written as:

$$\min_{a \in \mathbb{R}} a' a \text{ s.t. } \sup_{\beta \in \mathbb{R}, \gamma \in \Gamma} a' (w\beta + Z\gamma) - \beta \leq B \quad (3.9)$$

The optimal weight is then given by:

Theorem 3.1.1: Optimal Weight

Let π_{λ}^* be a solution to^a

$$\min_{\pi} \|w - Z\pi\|_2^2 \text{ s.t. } \text{Pen}(\pi) \leq t_{\lambda} \quad (3.10)$$

and suppose that $\|w - Z\pi\|_2 > 0$, $\text{Pen}(\cdot)$ is continuous, then the optimal weight solving 3.9 is

$$a_{\lambda}^* = \frac{w - Z\pi_{\lambda}^*}{(w - Z\pi_{\lambda}^*)' w}$$

with the bound

$$B = \frac{C}{t_{\lambda}} \cdot \frac{(w - Z\pi_{\lambda}^*)' Z\pi_{\lambda}^*}{(w - Z\pi_{\lambda}^*)' w}$$

Consequently, we have

- estimator

$$\hat{\beta}_{\lambda} = a_{\lambda}^* Y = \frac{(w - Z\pi_{\lambda}^*)' Y}{(w - Z\pi_{\lambda}^*)' w}$$

- worst-case bias

$$\overline{\text{bias}}_{\Gamma}(\hat{\beta}_{\lambda}) = C\bar{B}_{\lambda} = \frac{C}{\text{Pen}(\pi_{\lambda}^*)} \frac{(w - Z\pi_{\lambda}^*)' Z\pi_{\lambda}^*}{(w - Z\pi_{\lambda}^*)' w}$$

- variance of estimator

$$V_{\lambda} = \frac{\sigma^2 \|w - Z\pi_{\lambda}^*\|_2^2}{\left[(w - Z\pi_{\lambda}^*)' w \right]^2}$$

^aThis regression can be referred to as a regularized propensity score regression (but w_i need not be binary) with penalty $\text{Pen}(\pi)$

This result follows by applying Donoho (1994), Low (1995) and Armstrong and Kolesár (2018), rewriting 3.9

as a convex optimization problem.

A Proofs

A.1 Proof of Theorem 3.1.1

Following [Armstrong and Kolesár \(2018, Equation \(25\)\)](#), the modulus of continuity is given by

$$\omega(\delta) = \sup_{\beta, \gamma} 2\beta \quad \text{s.t. } \|w\beta + Z\gamma\|_2 \leq \frac{\delta}{2}, \quad \text{Pen}(\gamma) \leq C$$

Introducing a substitution (rescaling γ by β) $\pi = -\frac{\gamma}{\beta}$, get

$$\omega(\delta) = \sup_{\beta, \pi} 2\beta \quad \text{s.t. } \beta\|w - Z\pi\|_2 \leq \frac{\delta}{2}, \quad \beta\text{Pen}(\pi) \leq C \quad (3.11)$$

recall the optimization problem in Theorem 3.1.1:

$$\min_{\pi} \|w - Z\pi\|_2^2 \quad \text{s.t. } \text{Pen}(\pi) \leq t_\lambda$$

We can relate the two problems via the following logic: we want to make $\|w - Z\pi\|_2$ and $\text{Pen}(\pi)$ small so that large values of β satisfy the constraint of 3.11. Formally:

Lemma A.1

- If $\exists \pi \in \mathcal{G}$ s.t. $w = Z\pi$ and $\text{Pen}(\pi) = 0$, then $w(\delta) = \infty, \forall \delta \geq 0$ (automatic)
- **Otherwise:**
 - (i) $\forall \delta > 0$, the problem 3.11 has a solution $\beta_\delta^{mod}, \pi_\delta^{mod}$ with $\beta_\delta^{mod} > 0$. For $t_\lambda = \frac{C}{\beta_\delta^{mod}} = \frac{2C}{w(\delta)}$, π_δ^{mod} is also a solution to the penalized regression (3.10)

$$\min_{\pi} \|w - Z\pi\|_2^2 \quad \text{s.t. } \text{Pen}(\pi) \leq t_\lambda$$

with optimized objective

$$\|w - Z\pi\|_2 = \frac{\delta}{2\beta_\delta^{mod}} = \frac{\delta}{w(\delta)} > 0$$

- (ii) $\forall t_\lambda > 0$, the penalized regression above has a solution π_λ^* . Setting

$$\beta_\lambda^* = \frac{C}{t_\lambda}$$

$$\delta_\lambda = 2\beta_\lambda^* \|w - Z\pi\|_2 = \frac{2C}{t_\lambda} \|w - Z\pi\|_2$$

the pair $(\beta_\lambda^*, \pi_\lambda^*)$ solves the modulus problem 3.11 at $\delta = \delta_\lambda$, with optimized objective $w(\delta_\lambda) = \frac{2C}{t_\lambda}$, as long as $\|w - Z\pi\|_2 > 0$

Proof of Lemma A.1: we prove the lemma with the following steps:

A the penalized problem 3.10 has a solution:

Let $\mathcal{G}^{(0)}$ denote the linear subspace of vectors $\pi \in \mathcal{G}$ s.t. $Z\pi = 0$, $\text{Pen}(\pi) = 0$; let $\mathcal{G}^{(1)}$ be a subspace s.t. $\mathcal{G} = \mathcal{G}^{(0)} \oplus \mathcal{G}^{(1)}$. Then, we can write $\pi \in \mathcal{G}$ uniquely as $\pi = \pi^{(0)} + \pi^{(1)}$ where $\pi^{(0)} \in \mathcal{G}^{(0)}$, $\pi^{(1)} \in \mathcal{G}^{(1)}$.

Therefore, we have $Z\pi = Z\pi^{(1)}$, and

$$\begin{aligned} \text{Pen}(\pi^{(1)}) &= \text{Pen}(\pi^{(1)}) - \text{Pen}(-\pi^{(0)}) \leq \text{Pen}(\pi) \\ \text{Pen}(\pi^{(1)}) &= \text{Pen}(\pi^{(1)}) + \text{Pen}(\pi^{(0)}) \geq \text{Pen}(\pi) \end{aligned} \Rightarrow \text{Pen}(\pi^{(1)}) = \text{Pen}(\pi)$$

Then, 3.10 can be written in terms of $\pi^{(1)} \in \mathcal{G}^{(1)}$ only. The level sets of this optimization problem are bounded and closed (by continuity of the seminorm $\text{Pen}(\cdot)$), so it has a solution, which is also the solution to the original problem.

B the modulus problem 3.11 has a solution: for the problem 3.11, feasible values of β are bounded as:

$$\beta \leq \frac{\delta}{2} \cdot \frac{1}{\|w - Z\pi\|_2} \qquad \beta \leq C \cdot \frac{1}{\text{Pen}(\pi)}$$

i.e., β is bounded by the inverse of the minimum of $\max\{\|w - Z\pi\|_2, \text{Pen}(\pi)\}$ over π , and it is strictly positive. Hence, $\beta, \tilde{\pi}^{(1)}$ can be restricted to a compact set without changing the optimization problem.

C proof of statement (i): Proof by contradiction, if it's not true, then $\exists \tilde{\pi}$ s.t.

$$\text{Pen}(\tilde{\pi}) \leq \frac{C}{\beta_\delta^{\text{mod}}} \equiv t_\lambda, \qquad \|w - Z\tilde{\pi}\|_2 \leq \|w - Z\pi_\delta^{\text{mod}}\|_2 - v$$

then for some η , let $\tilde{\pi}_\eta = (1 - \eta)\tilde{\pi}$, we have

$$\begin{aligned} \|w - Z\tilde{\pi}_\eta\|_2 &= \|w - Z(1 - \eta)\tilde{\pi}\|_2 \\ &\leq \|w - X\tilde{\pi}\|_2 + \eta\|Z\tilde{\pi}\|_2 \\ &\leq \|w - X\pi_\delta^{\text{mod}}\|_2 - v + \eta\|Z\tilde{\pi}\|_2 \\ &\leq \frac{\delta}{2\beta_\delta^{\text{mod}}} - v + \eta\|Z\tilde{\pi}\|_2 \end{aligned}$$

Hence, $\exists \eta$ small enough, s.t.

$$\|w - Z\tilde{\pi}_\eta\|_2 < \frac{\delta}{2\beta_\delta^{\text{mod}}}, \qquad \text{Pen}(\tilde{\pi}_\eta) \leq (1 - \eta) \frac{C}{\beta_\delta^{\text{mod}}} < \frac{C}{\beta_\delta^{\text{mod}}}$$

therefore, by setting $\pi = \tilde{\pi}_\eta$, we can allow a strictly bigger β , which is a contradiction.

D proof of statement (ii): This result follows immediately.

Next, use Lemma A.1 to prove Theorem 3.1.1. Following [Armstrong and Kolesár \(2018\)](#), the class of bias-variance optimizing estimators is

$$\frac{\left(w\beta_\delta^{\text{mod}} + Z\gamma_\delta^{\text{mod}}\right)' Y}{\left(w\beta_\delta^{\text{mod}} + Z\gamma_\delta^{\text{mod}}\right)' w}$$

This is given by the **centrosymmetry** of the smooth function. As stated by [Armstrong and Kolesár \(2018\)](#), the functions that solve the single-class modulus problem can be taken to satisfy $g_\delta^* = -f_\delta^*$ under centrosymmetry. For the modulus 3.11, rewrite it as

$$w(\delta) = \sup \left\{ 2\beta : \beta\|w - Z\pi\|_2 \leq \frac{\delta}{2}, \beta \leq \frac{C}{\text{Pen}(\pi)} \right\}$$

since $f_\delta^* = -g_\delta^*$, $f_{M,\delta}^*$ is the zero function and $\hat{L}_{\delta,\mathcal{F}}$ is linear:

$$\hat{L}_{\delta,\mathcal{F}} = \frac{2w'(\delta; \mathcal{F})}{\delta} \langle K g_\delta^*, Y \rangle$$

this is the class of bias-variance optimizing estimators, given by

$$\frac{\left(w\beta_{\delta}^{mod} + Z\gamma_{\delta}^{mod}\right)' Y}{\left(w\beta_{\delta}^{mod} + Z\gamma_{\delta}^{mod}\right)' w}$$

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