Varying impacts of letters of recommendation on college admissions

Approximate balancing weights for subgroup effects in observational studies

Eli Ben-Michael

Harvard University

(joint work with Avi Feller and Jesse Rothstein)

RAND Center for Causal Inference Symposium, June 2021

- *2016:* UC Berkeley pilot program requests **letters of recommendation** (LORs) for undergrad admission
    - No LOR requirement at other UCs/CSUs
- *Goal:* Identify students from non-traditional backgrounds who might be overlooked
    - "Holistic review" of applicants
- *Concern:* Adverse impact on disadvantaged applicants, especially under-represented minority (URM) students

Chair of the UC Berkeley Academic Senate

*"**LORs conflict with UC principles of access and fairness**, because students attending under-resourced schools or from disadvantaged backgrounds will find it more difficult to obtain high-quality letters, and could be disadvantaged by a LOR requirement"*

Chair of the UC Berkeley Academic Senate

*"**LORs conflict with UC principles of access and fairness**, because students attending under-resourced schools or from disadvantaged backgrounds will find it more difficult to obtain high-quality letters, and could be disadvantaged by a LOR requirement"*

University Committee on Affirmative Action, Diversity, and Equity

*"The burden of proof rests on those who want to implement the new letters of recommendation policy, and should include a test of statistical significance demonstrating **measurable impact on increasing diversity** in undergraduate admissions"*

Chair of the UC Berkeley Academic Senate

*"**LORs conflict with UC principles of access and fairness**, because students attending under-resourced schools or from disadvantaged backgrounds will find it more difficult to obtain high-quality letters, and could be disadvantaged by a LOR requirement"*

University Committee on Affirmative Action, Diversity, and Equity

*"The burden of proof rests on those who want to implement the new letters of recommendation policy, and should include a test of statistical significance demonstrating **measurable impact on increasing diversity** in undergraduate admissions"*

UC Berkeley administration requested independent review of LOR impact [Rothstein, 2017]

Chair of the UC Berkeley Academic Senate

*"**LORs conflict with UC principles of access and fairness**, because students attending under-resourced schools or from disadvantaged backgrounds will find it more difficult to obtain high-quality letters, and could be disadvantaged by a LOR requirement"*

University Committee on Affirmative Action, Diversity, and Equity

*"The burden of proof rests on those who want to implement the new letters of recommendation policy, and should include a test of statistical significance demonstrating **measurable impact on increasing diversity** in undergraduate admissions"*

UC Berkeley administration requested independent review of LOR impact [Rothstein, 2017]

$\rightsquigarrow$ **LORs discontinued** before study results released

LOR Pilot Program: Subgroup Effects

Our question: Impact of submitting LORs on admissions

- Variation across pre-defined subgroups, especially URM status

→ Design an observational study; one of many potential cuts at this problem

LOR Pilot Program: Subgroup Effects

Our question: Impact of submitting LORs on admissions

- Variation across pre-defined subgroups, especially URM status

→ Design an observational study; one of many potential cuts at this problem

Challenge: Design the study for good overall and subgroup estimates

- Only optimizing for global balance → poor subgroup estimates
  - Ignores subgroup structure, assumes away heterogeneity
- Only optimizing for local balance → poor overall estimates
  - Potentially small errors compound across subgroups

LOR Pilot Program: Subgroup Effects

Our question: Impact of submitting LORs on admissions

- Variation across pre-defined subgroups, especially URM status

→ Design an observational study; one of many potential cuts at this problem

Challenge: Design the study for good overall and subgroup estimates

- Only optimizing for global balance → poor subgroup estimates
  - Ignores subgroup structure, assumes away heterogeneity
- Only optimizing for local balance → poor overall estimates
  - Potentially small errors compound across subgroups

Our paper: Balancing weights for subgroup analysis

- Partially pooled balancing weights, control both local balance and global balance
- *Dual:* IPW with hierarchical propensity score

LOR Pilot Program: Subgroup Effects

Our question: Impact of submitting LORs on admissions

- Variation across pre-defined subgroups, especially URM status

$\rightarrow$ Design an observational study; one of many potential cuts at this problem

Challenge: Design the study for good overall and subgroup estimates

- Only optimizing for global balance $\rightarrow$ poor subgroup estimates
  - Ignores subgroup structure, assumes away heterogeneity
- Only optimizing for local balance $\rightarrow$ poor overall estimates
  - Potentially small errors compound across subgroups

Our paper: Balancing weights for subgroup analysis

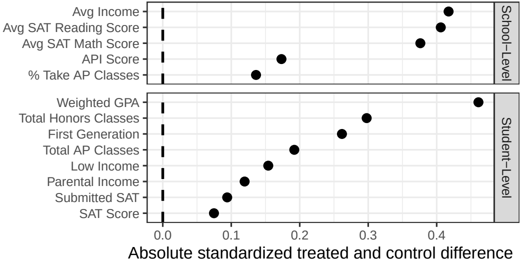
- Partially pooled balancing weights, control both local balance and global balance
- *Dual:* IPW with hierarchical propensity score

No evidence of differential impacts on URM applicants

Letters of Recommendation: Pilot Study

LOR Pilot Study: Overview

- Total $N = 40,541$ applicants in 2016
  [exclude athletes, other groups]
  - 14,596 invited to submit LORs
  - 11,143 submitted LoRs
- Two admissions readers
  - Scores of {No, Possible, Yes}
  - Admitted with 1-2 Yes votes
- Invitation to submit LORs:
  [+ funkiness due to timing]
  - First reader score of "possible"
  - Predicted possible score of >50%
    [nearly all URM]

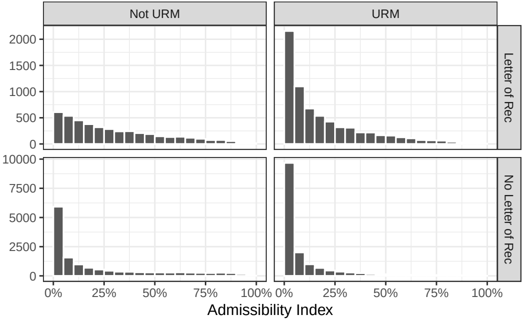


LoR Pilot Study: Subgroups

URM: Under-Represented Minority

- Low-income or first-gen college
- Underrepresented racial/ethnic group
- Low-performing high school

  [$\sim$ 55% of all applicants]



AI: Admissibility Index

- Predicted prob. of admissions using 2015 data
- Strong prognostic indicator!

Define subgroups by URM $\times$ AI bin

$+$ First reader score; college applied to

Setup and Background

Setup

For applicant $i = 1, \ldots, N$ observe

- Outcome $Y_i \in \mathbb{R}$ (admission)
- Treatment status $W_i \in \{0, 1\}$ (submit LoRs)
- Covariates $X_i \in \mathcal{X}$
- Group indicator $G_i \in \{1, \ldots, K\}$

Setup

For applicant $i = 1, \dots, N$ observe

- Outcome $Y_i \in \mathbb{R}$ (admission)
- Treatment status $W_i \in \{0, 1\}$ (submit LoRs)
- Covariates $X_i \in \mathcal{X}$
- Group indicator $G_i \in \{1, \dots, K\}$

Estimands: Overall ATT and subgroup CATTs

$$\tau = \mathbb{E}[Y(1) - \underbrace{Y(0)}_{\widehat{\mu}_0 = \sum \hat{\gamma}_i Y_i} \mid W = 1] \quad \text{and} \quad \tau_g = \mathbb{E}[Y(1) - \underbrace{Y(0)}_{\widehat{\mu}_{0g} = \sum_{G=g} \hat{\gamma}_i Y_i} \mid W = 1, G = g]$$

Setup

Strong ignorability (sensitivity analysis in paper)

$$Y(1), Y(0) \perp\!\!\!\perp W \mid X, G \qquad \text{and} \qquad e(X, G) \equiv P(W = 1 \mid X, G) < 1$$

Strong ignorability (sensitivity analysis in paper)

$$Y(1), Y(0) \perp\!\!\!\perp W \mid X, G \qquad \text{and} \qquad e(X, G) \equiv P(W = 1 \mid X, G) < 1$$

Many methods for subgroup effects under ignorability

- **Outcome model** and **design-based** approaches
- *Review:* 2018 ACIC data challenge [Carvalho et al., 2020]

Inverse Propensity Score Weighting identities, with known $e(x, g)$

$$\mu_0 \;=\; \mathbb{E}[\text{missing } Y(0) \mid \text{treated}] = \mathbb{E}\Big[\underbrace{\frac{e(x,g)}{1-e(x,g)}}_{\text{weights}}\; Y^{\text{obs}} \mid \text{control}\Big]$$

Inverse Propensity Score Weighting identities, with known $e(x, g)$

$$\mu_0 \;=\; \mathbb{E}[\text{missing } Y(0) \mid \text{treated}] = \mathbb{E}\Big[\underbrace{\frac{e(x,g)}{1-e(x,g)}}_{\text{weights}}\; Y^{\text{obs}} \mid \text{control}\Big]$$

$$\mathbb{E}[\text{covariates} \mid \text{treated}] = \mathbb{E}\Big[\underbrace{\frac{e(x,g)}{1-e(x,g)}}_{\text{weights}}\; \text{covariates} \mid \text{control}\Big]$$

Inverse Propensity Score Weighting identities, with known $e(x, g)$

$$\mu_0 = \mathbb{E}[\text{missing } Y(0) \mid \text{treated}] = \mathbb{E}\Big[\underbrace{\frac{e(x,g)}{1-e(x,g)}}_{\text{weights}} \; Y^{\text{obs}} \mid \text{control}\Big]$$

$$\mathbb{E}[\text{covariates} \mid \text{treated}] = \mathbb{E}\Big[\underbrace{\frac{e(x,g)}{1-e(x,g)}}_{\text{weights}} \; \text{covariates} \mid \text{control}\Big]$$

$\rightsquigarrow$ How to estimate weights?

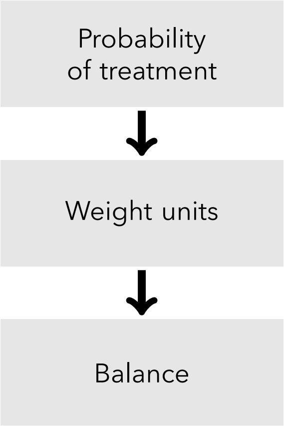
Background: Traditional IPW workflow

Goal: $\hat{e}(x, g)$ close to $e(x, g)$

1. **Directly** estimate $\hat{e}(x, g)$, via MLE, ML, etc.

2. Calculate weights $\hat{\gamma} = \frac{\hat{e}(x,g)}{1-\hat{e}(x,g)}$

3. **Indirectly** balance covariates

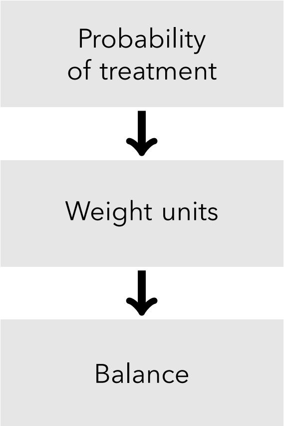


Background: Traditional IPW workflow

Goal: $\hat{e}(x, g)$ close to $e(x, g)$

1. **Directly** estimate $\hat{e}(x, g)$, via MLE, ML, etc.
2. Calculate weights $\hat{\gamma} = \frac{\hat{e}(x,g)}{1-\hat{e}(x,g)}$
3. **Indirectly** balance covariates

- Poor finite sample performance, esp with many covariates



Background: Balancing weights workflow

Goal: $\hat{\gamma}$ close to $\frac{e(x,g)}{1-e(x,g)}$

1. **Directly** estimate $\hat{\gamma}$ to balance covariates

2. **Indirectly** estimate $\hat{e}(x, g) = \frac{\hat{\gamma}}{1+\hat{\gamma}}$

Probability of treatment

$\uparrow$

Weight units

$\uparrow$

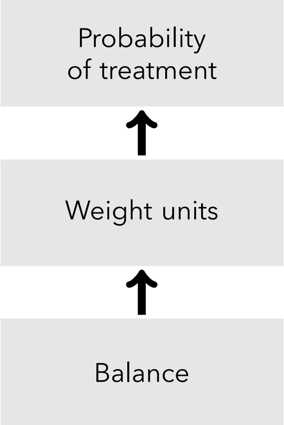
Balance

Background: Balancing weights workflow

Goal: $\hat{\gamma}$ close to $\frac{e(x,g)}{1-e(x,g)}$

1. **Directly** estimate $\hat{\gamma}$ to balance covariates
2. **Indirectly** estimate $\hat{e}(x,g) = \frac{\hat{\gamma}}{1+\hat{\gamma}}$

- Old history as raking and calibration in survey sampling with non-response
  [Deming and Stephan, 1940; Deville et al., 1993]
- New causal inference literature
  [Hainmueller, 2011; Zubizarreta, 2015; Athey et al., 2018; Chernozhukov et al., 2018]



Balancing weights to estimate subgroup effects

Balancing weights for local balance only

Error for effect in subgroup g

For outcome model $m_0 = \eta_g \cdot \phi(x)$; weighting estimator $\hat{\mu}_{0g} = \sum \gamma Y_i$

$$\text{error}_g \quad \leq \quad \|\eta_g\|_2 \left\| \text{Local Balance}_g \right\|_2 \quad + \quad \|\gamma\|_2$$

Can generalize to flexible outcome models [Hirshberg et al., 2019; Hazlett, 2020]

Balancing local balance only

Balancing weights for subgroup g

$$\min_{\gamma} \quad \|\text{Local Balance}_g\|_2^2 \quad + \quad \frac{\lambda_g}{2}\|\gamma\|_2^2$$

$$\text{s.t.} \quad \sum \gamma_i = 1, \quad \gamma_i \geq 0$$

Balancing local balance only

Balancing weights for subgroup g

$$\min_{\gamma} \quad \|\text{Local Balance}_g\|_2^2 \quad + \quad \frac{\lambda_g}{2}\|\gamma\|_2^2$$

$$\text{s.t.} \quad \sum \gamma_i = 1, \quad \gamma_i \geq 0$$

Challenge:

- Small subgroups can be hard to balance well
- Balancing subgroups separately $\rightarrow$ poor global balance

Balancing global balance and local balance

Partially Pooled Balancing Weights

$$\min_{\gamma} \quad \sum_{g} \|\text{Local Balance}_g\|_2^2 \quad + \quad \frac{\lambda_g}{2}\|\gamma\|_2^2$$

$$\text{s.t.} \quad \sum_{G_i = g} \gamma_i = n_{1g}, \quad \gamma_i \geq 0$$

$$\text{Global Balance} = 0$$

Balancing global balance and local balance

Partially Pooled Balancing Weights

$$\min_{\gamma} \quad \sum_{g} \|\text{Local Balance}_g\|_2^2 \quad + \quad \frac{\lambda_g}{2}\|\gamma\|_2^2$$

$$\text{s.t.} \quad \sum_{G_i = g} \gamma_i = n_{1g}, \qquad \gamma_i \geq 0$$

$$\text{Global Balance} = 0$$

- Overall errors depends on both global balance and local balance
- Further expand to control *differences* in local balance

⇝ *Tuning parameter:* Global parameter $\lambda \quad \Rightarrow \quad \lambda_g = \lambda / n_g$

Dual perspective: M estimation of treatment odds

Dual when optimizing for for local balance only

Population:
$$\underbrace{\frac{e(x,g)}{1-e(x,g)}}_{\substack{\text{inverse prop.}\\ \text{score weights}}} \sim \underbrace{\alpha_g + \beta_g'\phi(x)}_{\text{balancing weights}}$$

Dual perspective: M estimation of treatment odds

Dual when optimizing for for local balance only

Population:
$$\underbrace{\frac{e(x,g)}{1-e(x,g)}}_{\substack{\text{inverse prop.}\\ \text{score weights}}} \sim \underbrace{\alpha_g + \beta_g' \phi(x)}_{\text{balancing weights}}$$

Sample:
$$\min_{\alpha_g, \beta_g} \text{ regression loss } + \underbrace{\frac{\lambda}{2}\|\beta_g\|_2^2}_{\text{ridge penalty}}$$

Global balance constraint $\longleftrightarrow$ partial pooling in the dual problem

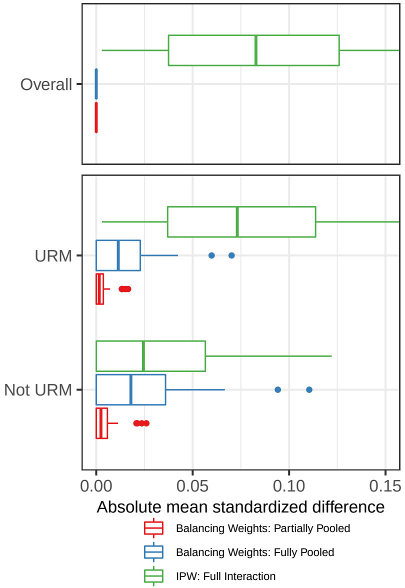
Dual for Partially Pooled Balancing Weights

$$\min_{\alpha_g, \beta_g, \mu_\beta} \ \text{regression loss} + \underbrace{\frac{\lambda_g}{2}\|\beta_g - \mu_\beta\|_2^2}_{\text{local} \to \text{global}}$$

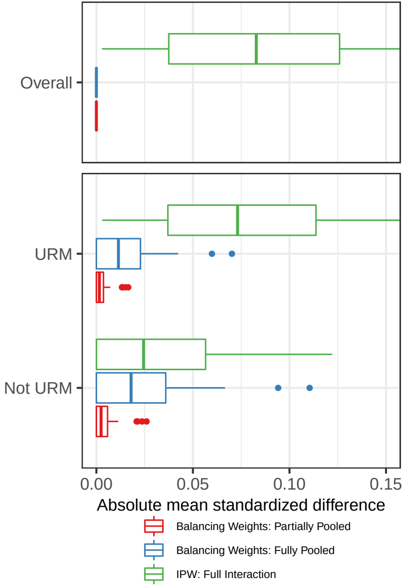
Partially pool local $\to$ global model: regularization *directly* related to imbalance

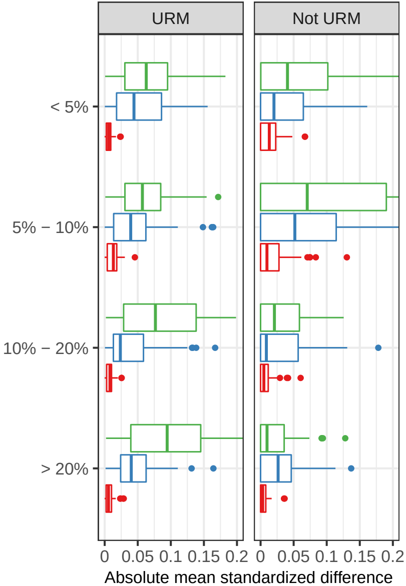
Differential impacts of letters of recommendation

Partially pooled balancing weights → improved balance



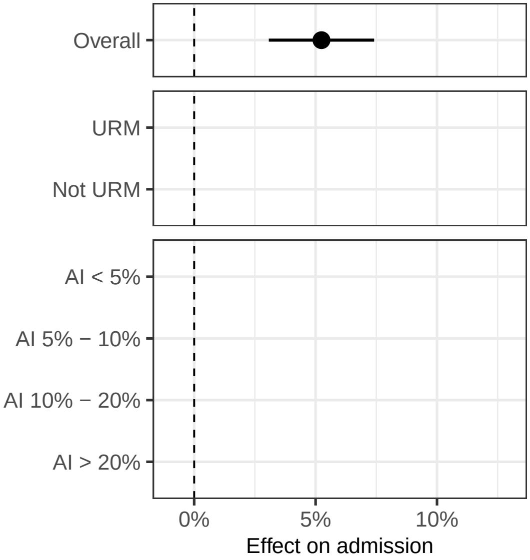
Partially pooled balancing weights → improved balance



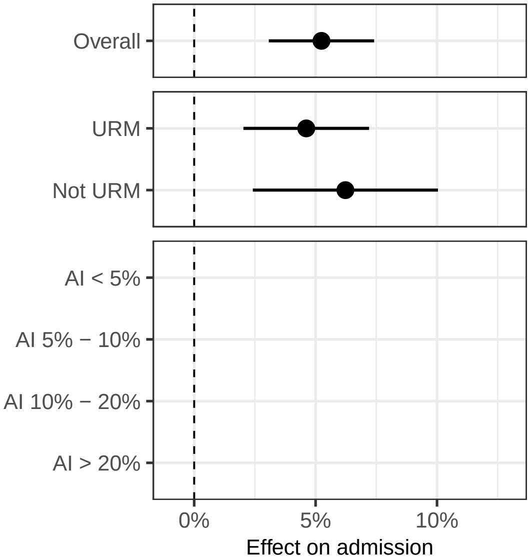


Large overall effect

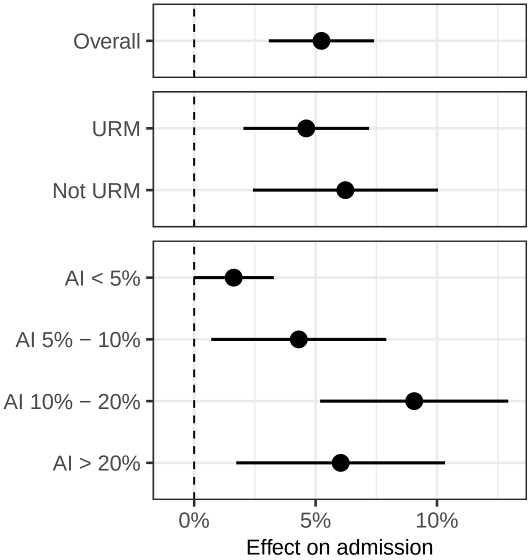
Baseline admissions rate ∼20%



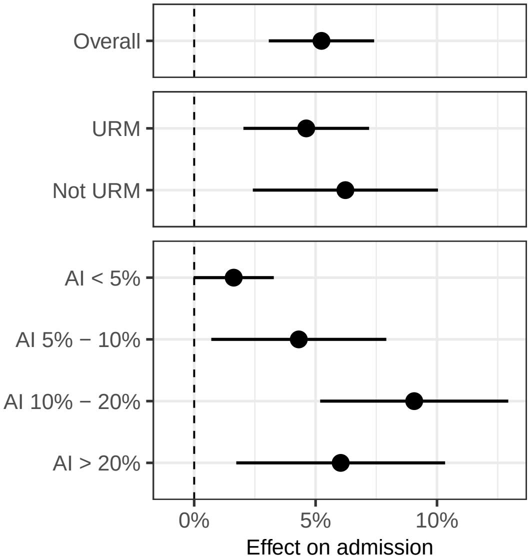
No differences by URM status

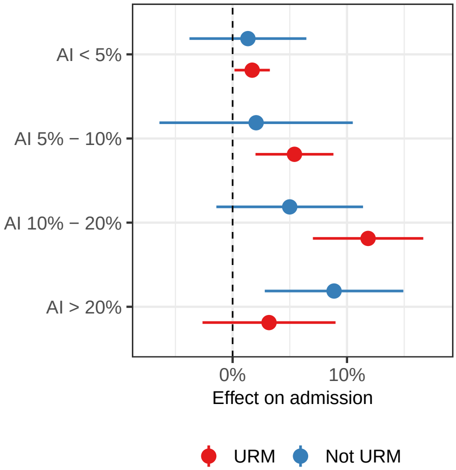


Large differences by Admissibility Index



Relative effect sizes flip





Recap: Varying Impacts of Letters of Recommendation

Partially pooled balancing weights

- Find weights that control both Local Balance and Global Balance
- Dual relation to partially pooled IPW
- R package `balancer`

→ No evidence of different impacts by URM status

Recap: Varying Impacts of Letters of Recommendation

Partially pooled balancing weights

- Find weights that control both Local Balance and Global Balance
- Dual relation to partially pooled IPW
- R package `balancer`

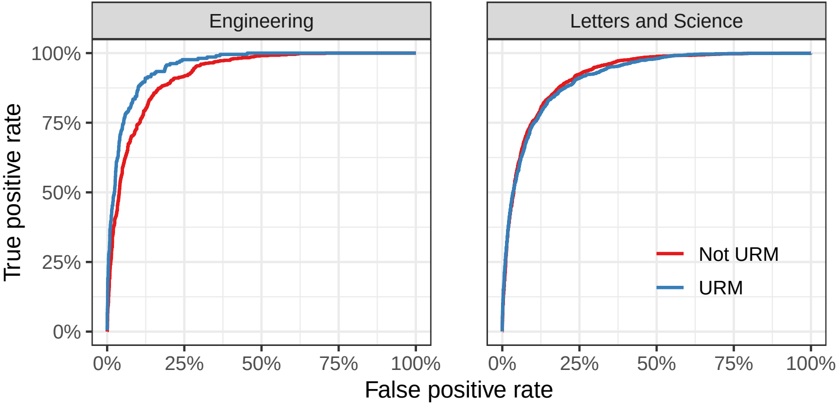
→ No evidence of different impacts by URM status

Thank you!

ebenmichael.github.io

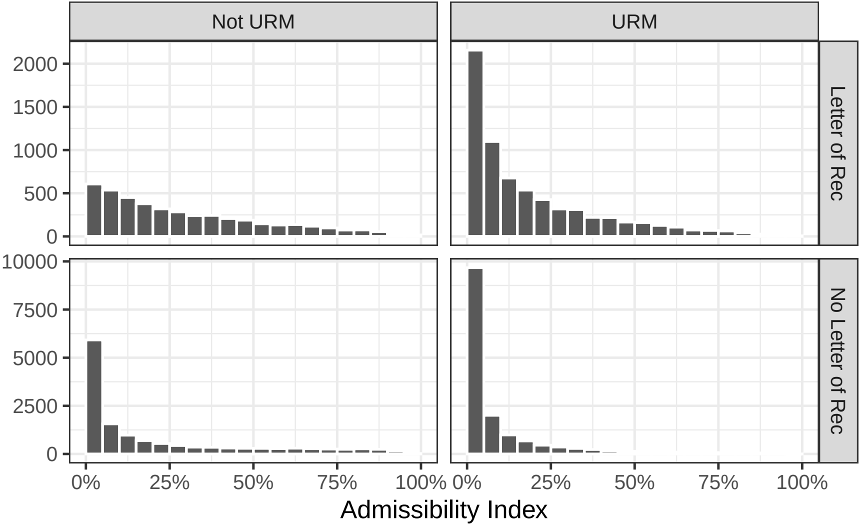
Appendix

Admissibility Index: a strong and simple prognostic

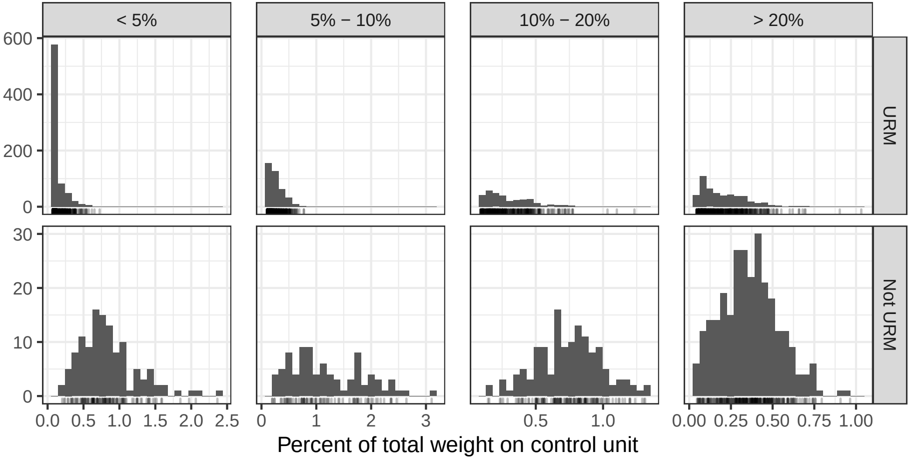


Use logisitic regression on 2015 applicant pool to predict admission for 2016 pool

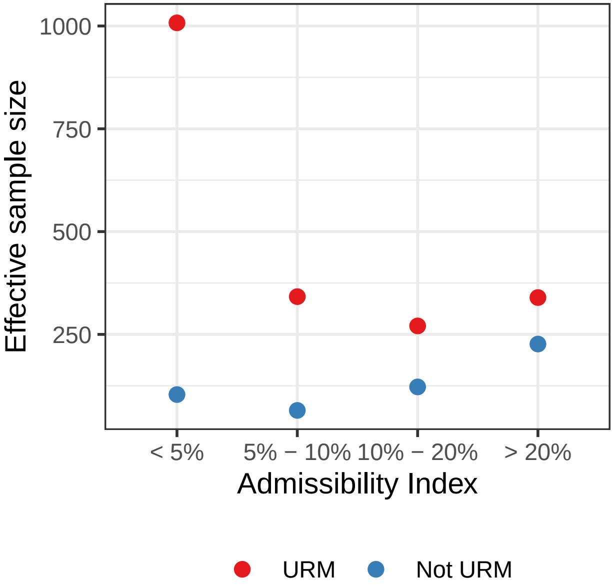
Heterogeneity across admissibility index



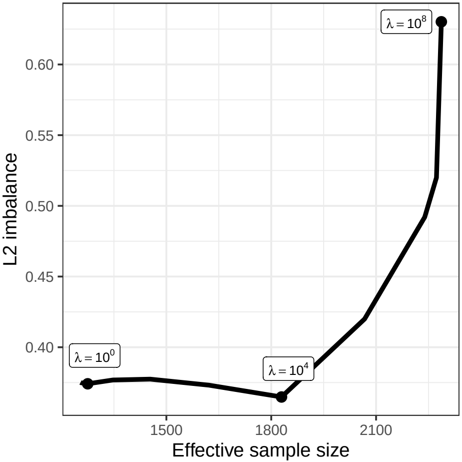
Distribution of the estimated weights



Effective sample sizes

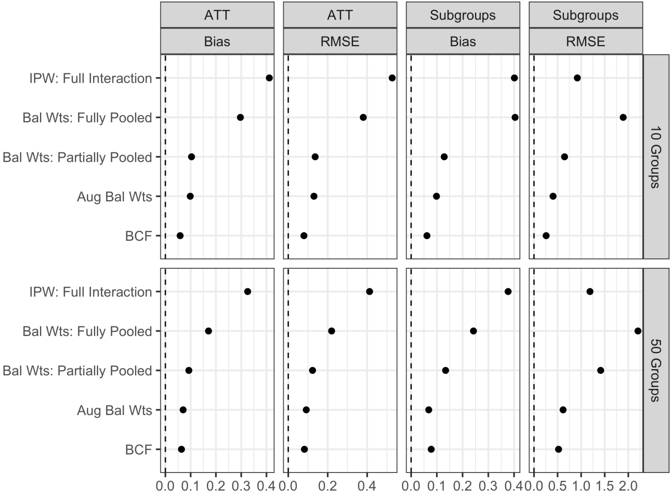


Hyperparameter tuning



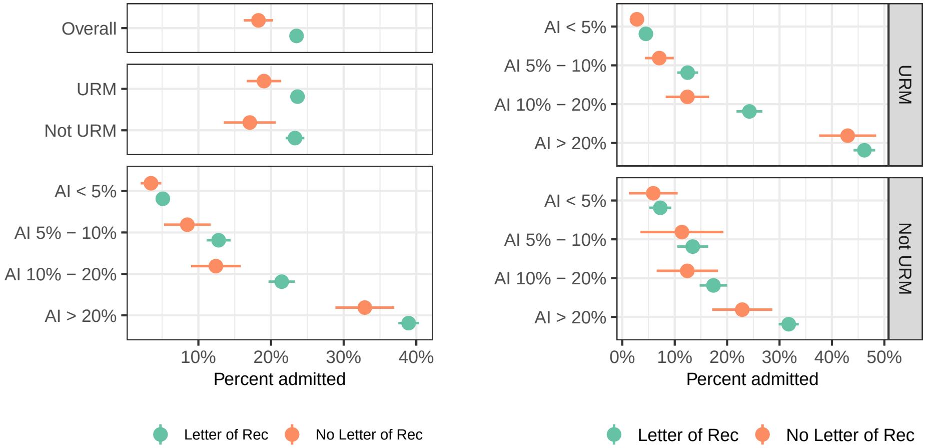
- Evaluate across a range of λ
- Gains in precision, comparable imbalance

Obligatory Simulation Study



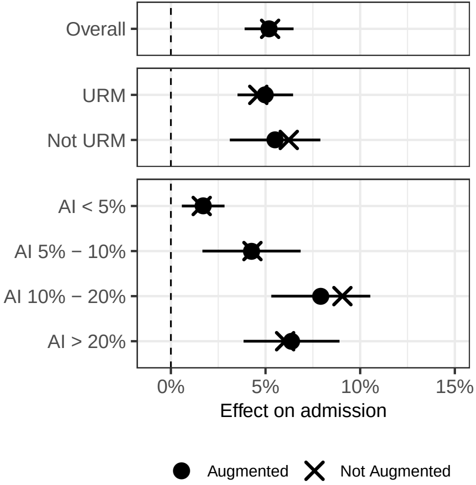
- Major gains relative to traditional IPW
- Comparable performance to ML methods; retain design-based advantages

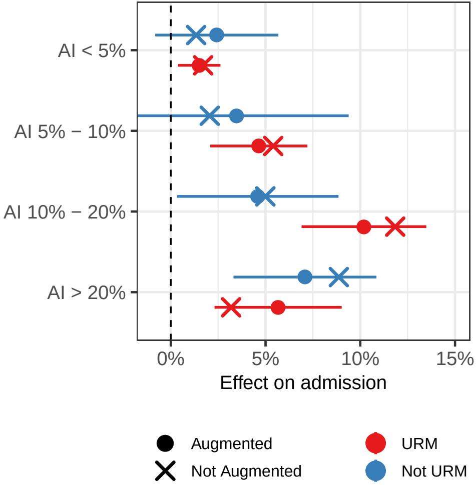
Estimated group means



Augmentation diminishes differences

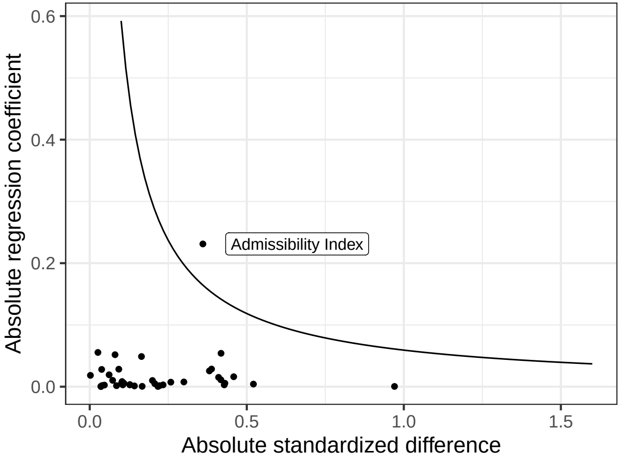
[Random forest outcome model]





Sensitivity to unmeasured confounding

- Adapt Soriano et al. [2021]
- Overall LOR effect still positive with $\Lambda = 1.1$
- Consistent with wide range of subgroup estimates



References I

Athey, S., Imbens, G. W., and Wager, S. (2018). Approximate residual balancing: debiased inference of average treatment effects in high dimensions. Technical report.

Chernozhukov, V., Newey, W., Robins, J., and Singh, R. (2018). Double/de-biased machine learning of global and local parameters using regularized riesz representers. *arXiv preprint arXiv:1802.08667*.

Deming, W. E. and Stephan, F. F. (1940). On a Least Squares Adjustment of a Sampled Frequency Table When the Expected Marginal Totals are Known. *The Annals of Mathematical Statistics*, 11(4):427–444.

Deville, J. C., Särndal, C. E., and Sautory, O. (1993). Generalized raking procedures in survey sampling. *Journal of the American Statistical Association*, 88(423):1013–1020.

Hainmueller, J. (2011). Entropy Balancing for Causal Effects: A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies. *Political Analysis*, 20:25–46.

Hazlett, C. (2020). Kernel balancing: A flexible non-parametric weighting procedure for estimating causal effects. *Statistica Sinica*.

Hirshberg, D. A., Maleki, A., and Zubizarreta, J. (2019). Minimax Linear Estimation of the Retargeted Mean.

Zubizarreta, J. R. (2015). Stable Weights that Balance Covariates for Estimation With Incomplete Outcome Data. *Journal of the American Statistical Association*, 110(511):910–922.