ECON 293 Homework 1: Commentary

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In this writeup I discuss results and include some key figures. Many further figures and all code are provided in the attached .html file. I worked with Luis Armona on the code and this commentary is written individually.

1

We chose to use data from "Does Price Matter in Charitable Giving? Evidence from a Large-Scale Natural Field Experiment", by Dean Karlan and John List (AER 2007). First we estimate the average treatment effect, pooling all treatments, on outcome variable total donation given via regression. We find a treatment effect of 0.1536, with a 95% confidence interval of $-0.0082, 0.3154$, consistent with the results in the paper.

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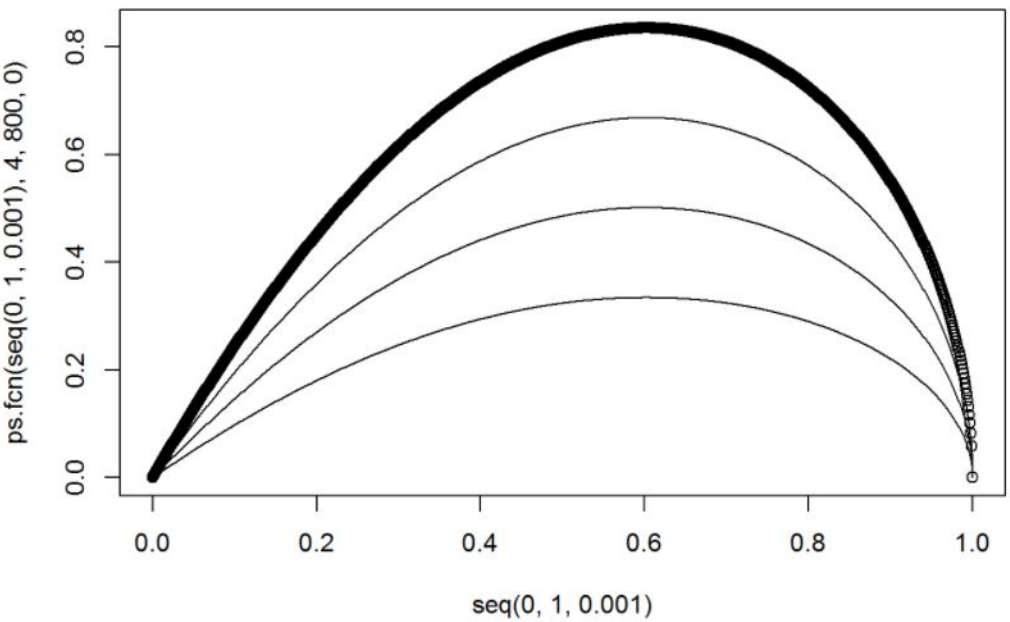
Our selection rule uses the fact that in the paper, it is demonstrated that treatment effects are highest among states which voted for Bush in the most recent election, and that this effect is biggest for the most marginal states. The probability of selection is chosen to be:

$$\psi = log(X_3 + sqrt(X_3^2 + 1))$$
$$Pr(S|W, X) = (1 - W) * (X_2 + 1) * (acos(X_1) * atan(X_1))/3 + W * (.01 + (-.01 * \psi^5 + \psi^3)/300)$$

Here, W is treatment, X_1 is the percentage who voted for Bush in the previous election, and X_1, X_2 are other covariates found to be correlated with treatment effects. This is a highly non-linear function involving several variables and hence unlikely to be recoverable by standard propensity score methods. 1 shows the shape of this function across proportion of Bush voters for a number of other covariate values.

We calculate $Pr(S|W, X)$ for each observation, and use a uniform random number generator to drop observations based on this. This selection means that we no-longer have a randomized experiment. Table 1 shows the full set of treatment effects estimated in this homework. The first

Figure 1: Selection rule



Notes: x-axis is number of votes won by Bush in previous election. This graph shows the shape of our selection rule for a number of different covariate values.

row shows the simple OLS on the full sample[1]. This could be considered the 'true' treatment effect, i.e. the treatment effect without selection. The estimate below of 0.3627 shows that when we restrict the sample according to our selection rule, the estimated treatment effect increases.

Overlap is demonstrated in Figure 2, which shows the true propensity scores for the treatment and control groups in the restricted sample.

These true propensity scores are calculated by Bayes theorem, combining our selection rule with the (unconditional) probability of treatment in the original sample.

Figure 3 is the histogram of the bias function as given in Athey, Imbens, Pham and Wager (2017). The expected bias is 0.061. As expected, since we have disproportionately included the treated with high treatment effects, the bias is generally positive. If we were to treat this as a random experiment, our treatment effect estimate would be biased upwards. This is consistent with what we see in Table 1.

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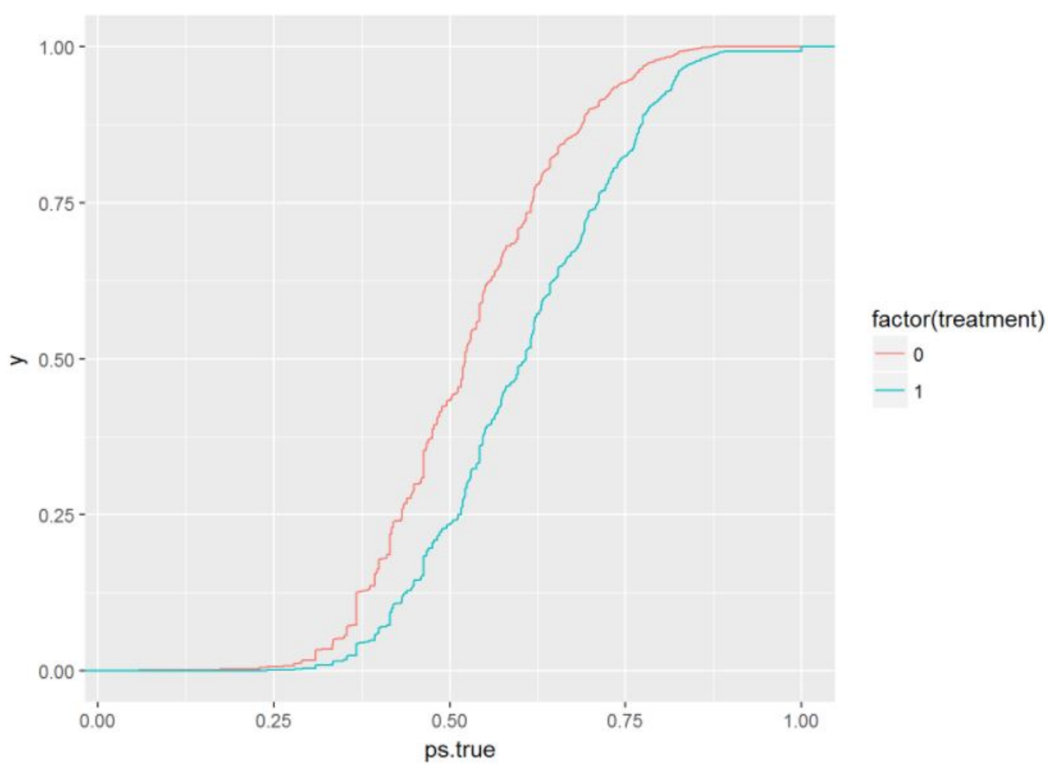
[1] note that this does not coincide with the previously-given estimate since we have restricted the sample to eliminate observations with missing covariates

Table 1: Estimated treatment effects

Estimator	Estimated treatment effect
Full sample simple OLS	0.1661
Restricted sample simple OLS	0.3627
PS Weighting	0.1665
OLS w/ Controls	0.1225
Traditional DR OLS w/ IPS Weights	0.0884
Regularized PS Weighted	0.1792
Classic Double Robust w/ Regularized PS	0.1574
Direct Lasso on Outcome	0.1138
Double Selection	0.1018
Lasso Residual-on-Residual	0.1123
Residual balancing	

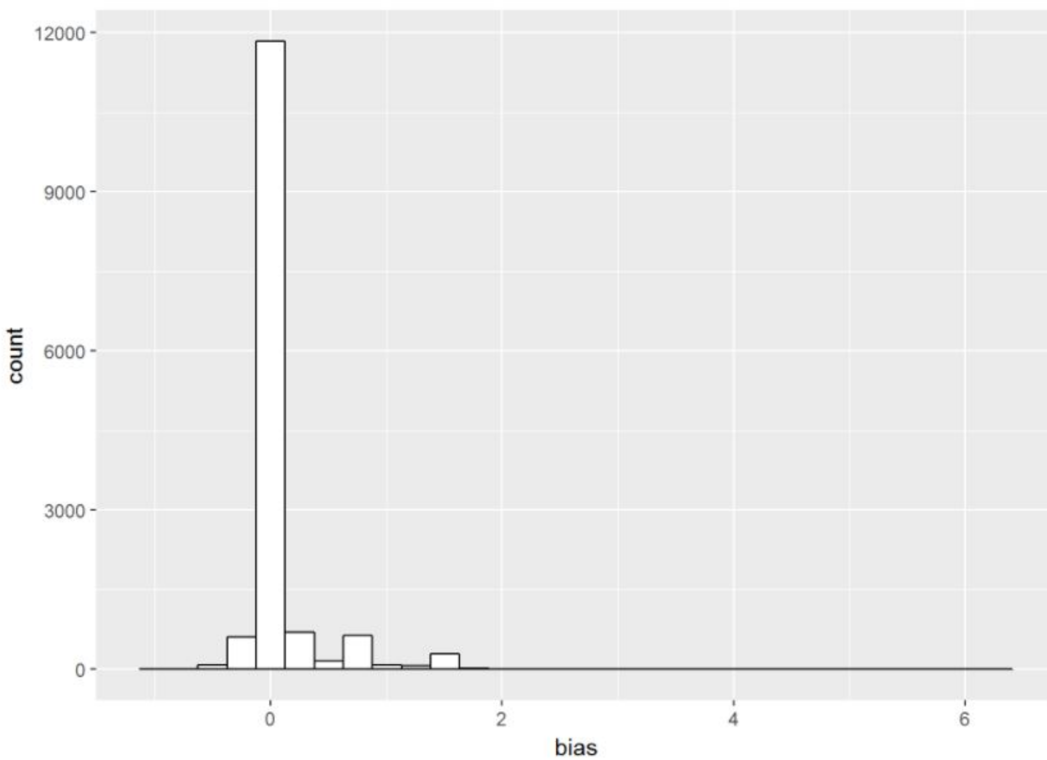
Notes: This table shows the various treatment effects estimated throughout this homework

Figure 2: Overlap



Notes: This graph shows the true propensity scores among treatment and control groups.

Figure 3: Bias Function



Notes: This graph shows the distribution of the bias, as given in Athey, Imbens, Pham and Wager (2017).