Method HW3

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Q2. Balance table

First, I run Levene's tests on homogeneous variance. Results show the variance of academic quality, athletic quality, and geo-location are not statistically different at 5% level across . the control and treatment groups[1]. Then, I proceed and run the t-test without correction. Results are reported below:

	Control	Treatment	Difference	t
Academic.Quality	0.52	0.47	0.05	(0.84)
Athletic.Quality	0.42	0.55	-0.13**	(-2.27)
Near.Big.Market	0.36	0.70	-0.34***	(-3.59)

It is pretty clear that groups are dissimilar, both in terms of athletic qualities and geo-locations. I do not test on donations because it is a post-treatment variable.

Q3. Data availability and propensity score model

If we do not know which variables are available and used in assigning treatment, then we cannot build a regression-based propensity score model. This is obviously true and is the contrapostitive statement of the question imposed.

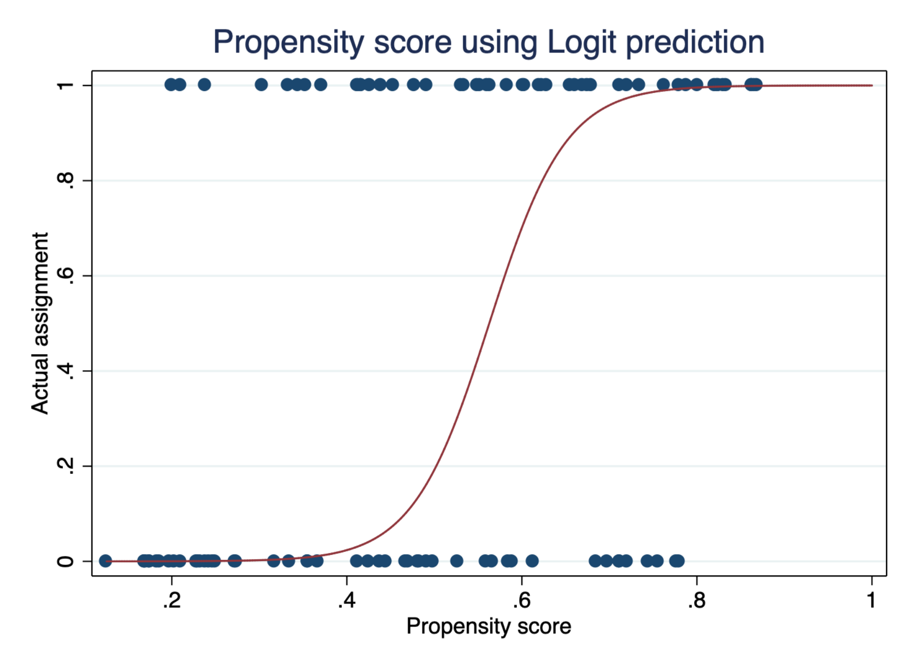
Q4. Data availability and propensity score model

I use logistic regression to produce the propensity scores. My model looks like the following:

$$Rank = \beta_1(academic.quality) + \beta_2(athletic.quality) + \beta_3(near.big.market) + \epsilon$$

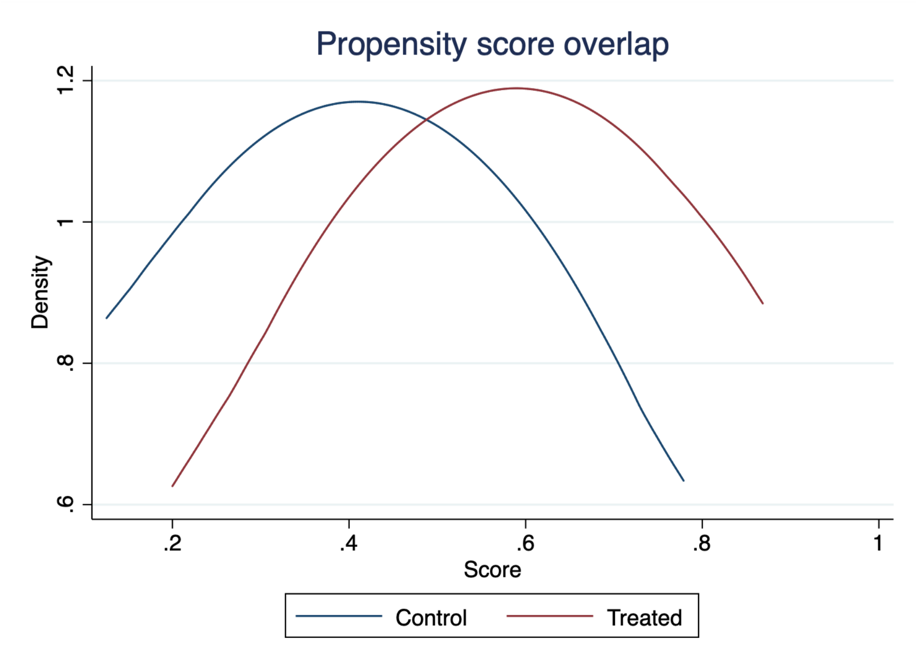
Produced propensity scores are plotted below against the inverse logistic distribution function.

[1] corresponding p-values are: 0.6, 0.9 and 0.7, all two-sided; results available upon request.



Q5. Overlaps

The overlap regions is between the propensity score of 0.2 and 0.8 as reported below. This region gives me 80 out of 100 observations.



Q6 and Q7. Blocking and estimation of treatment effect on donations

I use the same grouping strategy as the starter code - sort by propensity score then group data points into blocks of 4.
Different assignment of treatment yields different estimation results. I present two here. First, I assign treatment to the first and the second observations in each block. The treatment effect from ranking is identified only in the fully specified model (4), where I control academic quality, athletic quality, geo-proximity to metro area, as well as their interactions with the treatment. In particular, the treatment increases alumni donation by 341 dollars alone, but is offset quickly by higher athletic quality. My speculation is that alumni donors may be less willing to donate if their home team is already doing great (i.e. highly ranked). Other potential explanatory variables show mixed effect on donation. A geo-location effect is identified in model (2). Although it does not survive the block fixed effect model (3), it explains greater variance of donation nevertheless. Estimation results are reported in the table below:

Table 1: Treatement Effects of Ranking on University Alumni Donation

	(1)	(2)	(3)	(4)
	Baseline	Basedline	Block-FE	Blcok-FE
treatment=1	-57	-32	-13	341*
	(137)	(57)	(86)	(185)
Academic.Quality		54	-164	-142
		(102)	(768)	(811)
Athletic.Quality		133	780	1,077
		(119)	(1,625)	(1,670)
Near.Big.Market=1		1,122***	1,627	1,703
		(61)	(1,349)	(1,378)
TreatedXAcademic				-47
				(213)
TreatedXAthletic				-586**
				(269)
TreatedXMetro				-76
				(128)
Observations	80	80	80	80
Adjusted R^2	-0.011	0.829	0.825	0.833

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Then, I switch the assignments to the second and third observation in each block. Results are quite different this time. In particular, no independent treatment effect of ranking is identified. The only channel ranking can affect donation is through the interaction with geo-proximity to metro areas, where location itself is also strongly and robustly correlated. One possible explanation is that donors graduated from colleges in the urban areas are more likely to donate, especially if their home teams are doing poorly. Results from the second assignment are reported below:

Table 2: Treatement Effects of Ranking on University Alumni Donation, 2nd Assignment

	(1) Baseline	(2) Basedline	(3) Block-FE	(4) Blcok-FE
treatment=1	-15	-39	-35	271
	(137)	(56)	(57)	(193)
Academic.Quality		48	-235	-175
		(101)	(506)	(495)
Athletic.Quality		131	925	1,031
		(119)	(1,089)	(974)
Near.Big.Market=1		1,125***	1,751*	1,784**
		(61)	(898)	(822)
TreatedXAcademic				61
				(261)
TreatedXAthletic				-427
				(266)
TreatedXMetro				-240*
				(127)
Observations	80	80	80	80
Adjusted R^2	-0.013	0.829	0.826	0.832

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$