Assignment 3

Here, we aim to examine the effect of being ranked on alumni donations the following year. To address the sole effect of being ranked on alumni donations, we want to make sure that treatment and control groups are identical (or almost identical) in every possible way except for the treatment assignment (i.e., being ranked). Therefore, differences in covariates between the control and treatment groups are analyzed to ensure that the average characteristics for treatment and control are similar. Below is the balance table indicating whether the treatment and control groups are similar in observable characteristics: 1) Academic quality, 2) Athletic quality, and 3) Near big market.

Table 1. Balance Table

	Control	Treatment	Difference
Academic Quality	0.515	0.466	0.049
Athletic Quality	0.424	0.551	-0.127**
Near Big Market	0.360	0.700	-0.340***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table shows the results from t-test comparing academic quality, athletic quality, and location of control (i.e., unranked schools) and treatment (i.e., treated schools) groups and analyzing the significance of the differences.

Results indicate that meaningful differences between treatment and control groups exist in athletic quality and location (i.e., whether the college is located near a large metropolitan area). On average, the treatment group has higher athletic quality and is more likely to be located in large metropolitan areas. Such differences in observable characteristics are a severe threat to causal inference regarding the effect of being ranked on alumni donation since the treatment assignment is not the only difference between the control and treatment groups. If they are different in many ways, we cannot claim that the variation in alumni donation is driven by the effect of being ranked. What if graduates from colleges in a metropolitan area earn more income compared to those from colleges in a rural area, and such a difference in average income affects the amount of alumni donations?

To ensure the similarity between the control and treatment groups, I will match samples based on a propensity score. Propensity score matching can be advantageous in this setting as we have data on the athletic quality of each college, which may predict the treatment assignment (being ranked). If researchers can use variables that determine the treatment assignment, the propensity score becomes more credible since it is calculated in the same way as the real assignment. Thus, we build a logit model that predicts which colleges were ranked and predict the probability of the treatment using propensity score. The results of logit regression are shown below.

Table 2. Logit regression

	(1)
	Ranked (2017)
Ranked (2017)	
Academic Quality	-0.884

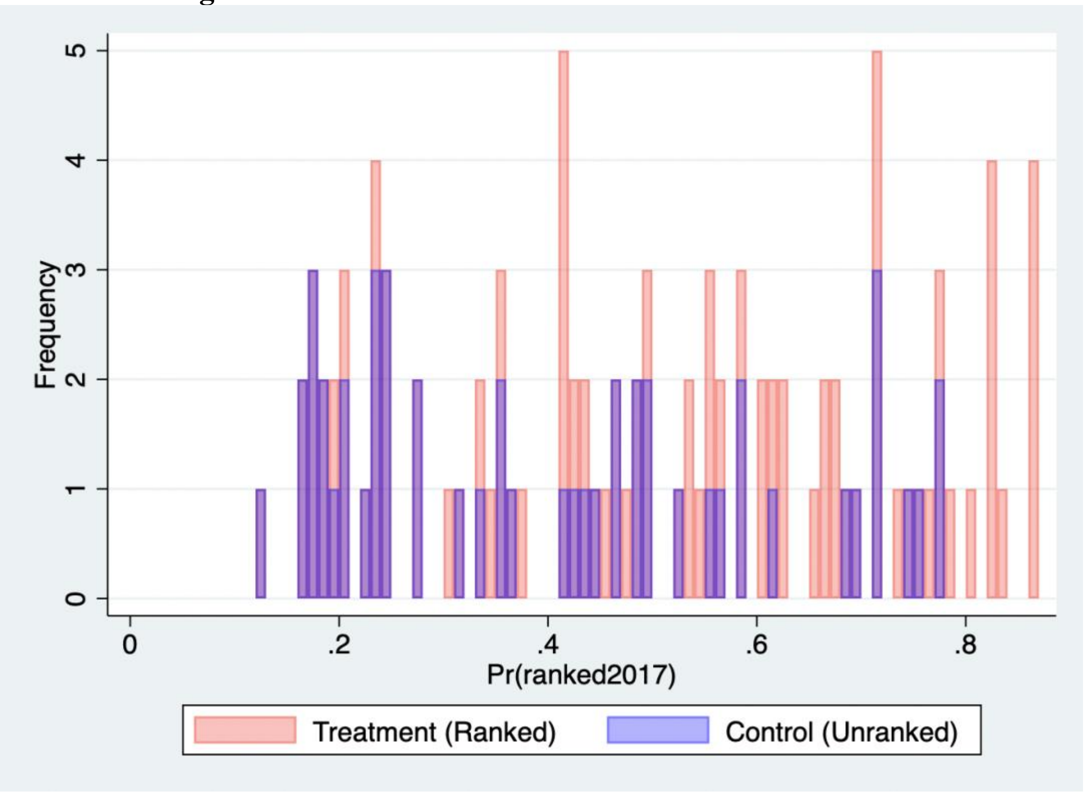
	(-1.13)
Athletic Quality	1.964*
	(2.44)
Near Big Market	1.615***
	(3.52)
_cons	-1.378*
	(-2.14)
N	100

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table shows the results from logit regressions analyzing the effect of academic quality, athletic quality, and location on being ranked (ranked=1, unranked=0).

Based on the logit model, we calculate the propensity score for treatment assignment. The stacked histogram below shows the overlap between control (i.e., unranked) and treatment (i.e., ranked) groups. It turned out that unranked colleges with propensity scores below 0.3 would hardly find the matching treated sample, while ranked colleges with propensity scores above 0.7 also have no great matching untreated sample.

***Stacked histogram**



Then, I blocked samples based on propensity score. I made 10 blocks with 100 samples and ran the regression analyzing the effect of being ranked on alumni donations the following year while adding block-fixed effects and controlling for academic quality, athletic quality, and location. Being ranked has a positive and statistically significant (p-value<0.00) effect on alumni donations the following year. It turned out that, on average, ranked schools get $500,000 more alumni donations the following year compared to unranked schools. Therefore, the results suggest that alumni donation can be an incentive to explain why universities enter the sports entertainment business.

Table 3. The effect of being ranked on alumni donations the following year

	(1) Alumni Donations (2018)
Ranked (2017)	500.5*** (2141.35)
Academic Quality	100.2*** (133.27)
Athletic Quality	49.72*** (29.94)
Near Big Market	999.5*** (757.56)
0.block	0 (.)
1.block	0.356 (0.65)
2.block	0.0539 (0.07)
3.block	-0.355 (-0.34)
4.block	0.343 (0.28)
5.block	0.190 (0.13)
6.block	-0.167 (-0.10)
7.block	0.708 (0.36)

8.block	0.421
	(0.19)
9.block	0.364
	(0.14)
10.block	0.918
	(0.31)
_cons	-0.0432
	(-0.11)
N	100

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table shows the results from OLS regressions analyzing the effect of being ranked on alumni donations the following year. Block-fixed effect included.