1. Balance Table

```
\begin{tabular}{l*{6}{c}}
                    &     Control&   Treatment&  Difference   \\
\hline
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***\\
\end{tabular}
```

My computer doesn't support Latex so I can't get a clear version.

2. Comment

The treatment and control are not similar. They are different at athletic quality and the distance between school and big market.

We can use propensity score to control these differences, by building propensity score based on different features and controlling for the score.

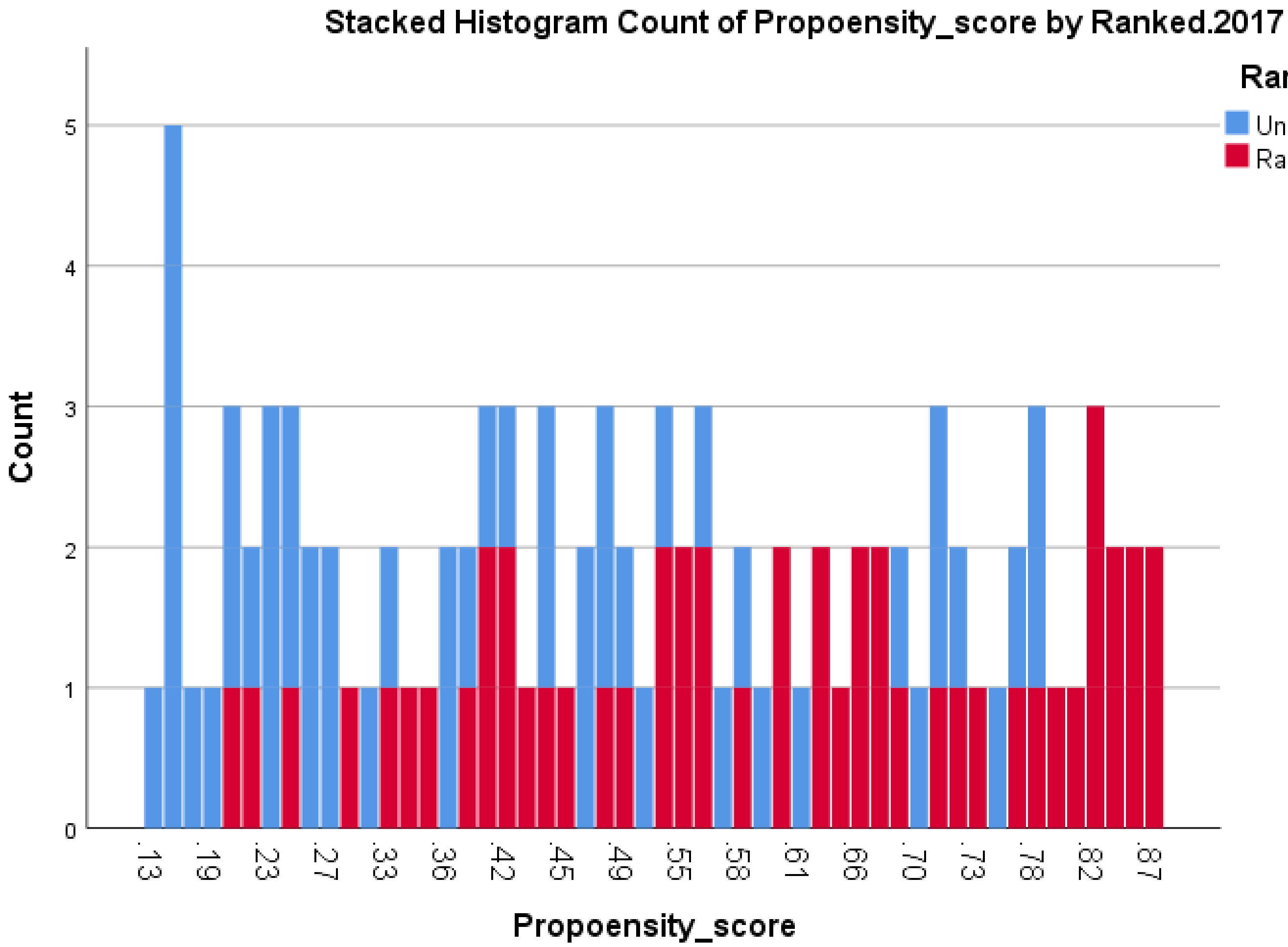
3. Propensity Score Model

	Ranked.2017
Ranked.2017	
Academic.Quality	-.88
	(.78)
Athletic.Quality	2**
	(.81)
Near.Big.Market	1.6***
	(.46)
Constant	-1.4**
	(.65)
Observations	100
R^2	

Standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01

4. Stacked Histograms



5. Treatment effect

	Alumni.Donations .2018
Ranked.2017	478***
	(73)
block=0	0
	(.)
block=1	-28
	(220)
block=2	-15
	(221)
block=3	-11
	(221)
block=4	-1.6
	(221)

block=5	5.6
	(220)
block=6	6
	(223)
block=7	-7.7
	(223)
block=8	274
	(223)
block=9	518**
	(227)
block=10	513**
	(223)
block=11	759***
	(223)
block=12	-1.2
	(221)
block=13	481**
	(223)
block=14	984***
	(227)
block=15	771***
	(223)
block=16	740***
	(223)
block=17	1,010***
	(232)
block=18	1,016***
	(232)
block=19	1,008***
	(221)
block=20	1,040***
	(223)
block=21	1,023***
	(221)
block=22	1,015***
	(227)
block=23	999***
	(232)
block=24	995***
	(232)
block=25	1,009***
	(341)
Constant	81
	(166)

Observations	100
R^2	0.848

Standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01

We could see that, after controlling for propensity issue, the rank2017 still significantly predict the alumni donation. So this result partially support the hypothesis in the introduction part.