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

**Note:** This table reports the means and the differences between the means of our treatment and control groups for a set of observable characteristics. The table clearly shows that average athletic quality is significantly higher in the treatment group (ranked colleges in 2017). Similarly, as indicated by *Near Big Market*, a larger proportion of the treatment group is also located near big cities (0.700) compared to the control group (0.36). Therefore, the distribution of our sample is not balanced across the control and treatment groups for athletic quality and a college’s proximity to a large metropolitan area. This indicates that there was some non-random selection into which college was ranked – colleges with high athletic quality and those near a large metropolitan area were more likely to be ranked.

Since colleges of higher athletic quality and those near metropolitan areas are more likely to be ranked (as indicated by Table 1), my propensity score model for predicting whether a college was ranked or not should include both. Additionally, although the differences between academic quality for the control and treatment groups are not statistically significant, I would still include it in my prediction model as it is possible that agents use information on academic quality to assign rankings. Propensity scores are more appropriate when we can predict the scores based on all the characteristics that agents who assign the treatments are able to use in their assignment, and I would therefore include all the variables in Table 1 build our propensity score model. Ideally, it would therefore be helpful to include additional information that agents also use to develop rankings, including e.g., whether the college recently won a major tournament, the number of high-performing athletes in its team, etc., as such nuanced information that is available to agents is unlikely to be captured by the 0-1 *athletic quality* variable. Not being able to include additional information that agents have access to makes our propensity score model biased.

I next build a propensity score model using logit regression. I predict the probability of being ranked using three variables listed in table 3. The resulting stacked histogram which shows the overlap between the ranked and unranked schools is available below:

**Figure 1.** Stacked histogram showing the overlap between ranked and unranked schools.



**Note:** The histogram above reports the predicted probability distribution of ranked and unranked schools. The probability estimates were calculated using logit regression. As the chart clearly indicates that there is no overlap beyond Propensity Score (Ranked) > 0.8, I drop those observations for my subsequent model.

**Table 2.** The treatment effect of being ranked on alumni donations, block-fixed effects included.

|  |  |
| --- | --- |
|  | Alumni Donations (2018) ('000 dollars) |
| Ranked (2017) | 500\*\*\* |
|  | (.27) |
| Academic Quality | 102\*\*\* |
|  | (1.9) |
| Athletic Quality | 47\*\*\* |
|  | (4.1) |
| Near Big Market | 997\*\*\* |
|  | (3.4) |
| Observations | 90 |
| *R*2 | 1.000 |

Standard errors in parentheses

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

**Note:** The table above reports our regression results of alumni donations a school received in 2018 as a function of the school’s ranking in 2017, academic quality, athletic quality, and proximity to a large metropolitan area (*Near Big Market*). As the model includes block-fixed effects such where each block included 4 observations (except the first and last blocks, both of which included 3 observations). Standard OLS standard errors are reported.

The results suggest that being ranked in 2017 increases alumni donations in 2018 by about $500,000. As the schools are matched with other schools into a block of 4 schools based on observable characteristics that predict their likelihood of being ranked, assuming that we are not excluding additional information that agents use to determine college rankings, this model suggest that being ranked causes alumni donations to be higher in the subsequent year by $500,000 on average.