How do University Rankings affect Universities?
Evidence from U.S. News Best College Rankings

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1 Introduction

A small body of literature originating around the new millennium suggests that university rankings influence the admission process and outcome of the ranked universities. Some of the most popular and far-reaching university rankings are made by the media company U.S. News and World Report (USN hereafter). Dating back to 1983, the USN university ranking has manifested its standing in higher education despite much criticism of its underlying ranking methodology. Earlier works report that a better placement in the USN ranking has positive effects on the number of applications that a university receives, the average SAT score of the incoming freshmen class, the percentage of students coming from the top 10% of their high school class, as well as the percentage of admitted students that eventually enroll. Beyond that, universities become more selective when their ranking improves, as suggested by a lower admission rate.

In this paper, I study the effects of a university's rank in the USN Best National Universities Ranking on a range of admission outcomes. These are the average SAT score at the university, the number of applications, admissions, and enrollments, as well as the admission rate, yield rate, and official tuition fees. My data sample is a panel of 118 high-ranked U.S. universities containing information on their USN ranking placements throughout 2008–2015 in addition to rich administrative data at the university level from the Integrated Postsecondary Education Data System (IPEDS), a data-providing branch of the U.S. Departement of Education.

The empirical analysis has two parts. In the first part, I estimate the expected effect of a drop by one rank, which I refer to as the baseline ranking effect. This is done with a standard fixed effects approach controlling for possible unobserved heterogeneity. Furthermore, this part includes several checks for heterogeneous effects in terms of the control and size of the studied universities as well as in terms of the relative position of the rank. In the second part, I access whether universities benefit from being listed on the first page of the rankings' print edition compared to being listed on the next, less conspicuous page. This is largely motivated by other works that found significant boosts to the affected universities when they managed to be ranked among the top 50, the cutoff to appear on the front page of the print edition of the USN ranking.

My main findings for the baseline ranking effect suggest that universities have a significantly lower percentage of admitted students that will enroll at a university in the year after a university dropped in the ranking. I find that the baseline effect for the average SAT score and the tuition fee is considerably different between private and public universities. The baseline ranking effect also differs with respect to the relative position of the rank. Universities that drop a rank within the top 25 are significantly stronger affected than universities that drop a rank within worse ranks. Even though the effect size varies in absolute magnitude for the SAT score and the number of enrollments, most of the reported effect sizes are so small that the impact of the placement in the ranking is almost negligible unless a university caught up substantially.

Since the effect of being ranked among the top 50 is essentially a rule-based treatment assignment, the second part of my empirical analysis employs a regression discontinuity (RD) approach. My findings for a frontpage effect are somewhat dull compared to earlier results. I find that whether universities end up on the first or second page of the printed USN ranking does not matter for any of the admission outcomes in my analysis.

My research contributes to the niche body of literature on the effect of university rankings. Since most of the earlier works study the impact of the USN ranking on the admission and yield rate without separate data on admissions or enrollments, my results alleviate this by allowing estimations of potential effects on these metrics in a disentangled way. Moreover, my data panel contains information on the USN ranking placements from more recent years and can thus provide insights on the development of the USN ranking and its imposed effect on universities' admission processes throughout the years.

The remainder of this paper is organized as follows: Section 2 provides a summary of the aforementioned earlier contributions and other related works on this topic. In Section 3, I give some historical background information on the USN ranking and briefly discuss criticism voiced by several authors. Section 4 provides a thorough summary of my data sample, while Section 5 and Section 6 deal with my empirical strategy and results. Lastly, Section 7 concludes with the most important findings of this paper.

2 Related Literature

This research is primarily related to the literature on university rankings and their imposed effects on various university admission outcomes. Since the new millenium, a handful of publications have studied how universities and applicants respond to university rankings. Due to similarities in the data sample, dependent variables, and estimation techniques, this paper is most closely related to Meredith (2004), Bowman and Bastedo (2009), Luca and Smith (2013), as well as Monks and Ehrenberg (1999).

Meredith (2004) uses USNWR rankings from 1990 to 1999 to estimate effects on

233 national doctoral universities' average SAT scores, admission rates, the percent of students coming from the top 10% of their high school class, grants, gifts, and demographic composition. Since U.S. News only assigned numerical rankings to the best 25 universities before 1996 (extended to the best 50 after 1996), the estimates capture the effects of rank movements within cohorts ranked between 1-25 and 26-50 separately. The specified model also incorporates dummies for being ranked in either of the first four quartiles. The results suggest that universities in the first quartile had a 4% points lower admission rate than universities in the second quartile in the following year. The difference diminished with higher quartiles, i.e., universities in the third quartile only had a 1% point higher admission rate than universities from the second quartile. The baseline one-rank effect was not significantly different from zero for movements within the top 25 but resulted in a significant 0.15% point increase in admission rates for a one-rank gain within ranks 26-50.[1] Similar observations are reported for the SAT score as the dependent variable—although the results had only significant implications in the sample of public universities. The baseline one-rank effect was not significant, but second-quartile (third-quartile, fourth-quartile) universities had a 19 (25, 40) points lower SAT score than first-quartile universities in the following year.

Bowman and Bastedo (2009) use U.S. News ranking data from 1997 to 2004. Their sample consists of national universities and liberal arts colleges that appeared in the top 50 at least once in these years, which is the cutoff to appear on the front page of the U.S. News print edition. Their study aims to quantify this frontpage effect as well as rank movements within the top 25 and top 26-50 on a range of admission outcomes in the following year. These outcomes include the 25 percentile of SAT scores, the proportion of students from the top 10% of their high school class, the number of applications, the admission rate, and the yield rate. They report a considerable front-page effect. In years after reaching the top 50, universities exhibit a 3.6% point decrease in admission rates, a 2.3% point increase in top-10% high school students, and a 4% increase in the number of applications. They note, however, that this effect may be driven by liberal art colleges. Once the model is estimated for national universities and liberal arts colleges separately, this effect changes. National universities experience significant front page effects only for the students coming from the top 10% of their high school class (4% point increase) and for the SAT score (12 point decrease). They note that the decrease in SAT scores is likely influenced by a single university, given that their sample contains only few universities that experience a change in front page status over

[1] Meredith (2004) constructed the ranking variable with a negative sign so that a numerically higher realization corresponds to a "better" rank.

the years. For the baseline rank effect, the results suggest that a one-rank improvement increases the SAT score by 1.2 points and the number of applications by 0.3%.[2] These effects are slightly more pronounced when only the top 25 universities are considered.

Luca and Smith (2013) study how rank changes affect the number of applications a university receives, admission rate, yield, the average SAT score of students, and the proportion of top 10% high school class students. Their sample consists of the top 50 universities as ranked by U.S. News from 1990 to 2000. In addition, they also examine whether the way in which the rankings are presented influences these results by exploiting a publication change from 1995 whereby the top 26-50 universities each received their own rank as opposed to only being labeled a top 26-50 university. They find that a drop by one rank leads to a 1-2% decrease in the number of applications a university receives and a 0.013-0.034% point increase in the admission rate, but no significant effects in terms of yield, SAT, or the percentage of top 10% high school class students.[3] Furthermore, the way in which the rankings are presented matters for student's application decisions. When the rankings are salient (each university has its own rank), applications decrease by 0.8-1% when a university drops one spot in the rankings. However, when the rankings are opaque (each university is labeled as a top 26-50 university but the ranking is in alphabetical order), applications are unaffected by changes in ranks.

Monks and Ehrenberg (1999) investigate whether U.S. News rankings impact a university's admission rate, yield, average SAT, and tuition. Their data set covers the ranks of 30 universities from 1987 to 1997—16 are among the top 25 national universities, one is among the top 26-50, and the remaining 13 are among the top 25 Liberal Arts Colleges as per the 1998 rankings. Like previous papers, they use lagged rank as the main explanatory variable of interest and employ a fixed effects approach controlling for time-invariant university-specific effects and year effects common to all universities. The results indicate that a one rank decrease in the ranking results in a 0.4% point increase in the admission rate and a 0.17% point decrease in the percentage of admitted students who enroll. A decline in rank additionally leads to a reduction in the average SAT of the student body, with the effect being stronger, the better the rank of the university.[4] With respect to tuition, the estimates suggest that universities reduce their

[2] Again, the rank variable is coded such that a higher rank corresponds to a preferable ranking placement.

[3] Luca and Smith (2013) use the top 25 sample in their baseline regressions. These results are therefore based on rank movements within top 25 universities.

[4] No definitive magnitude can be reported for the SAT since the regression also includes the squared rank. The size of the estimates are $\hat{\beta}_{Rank} = -2.777$ for Rank and $\hat{\beta}_{Rank^2} = 0.086$ for Rank^2.

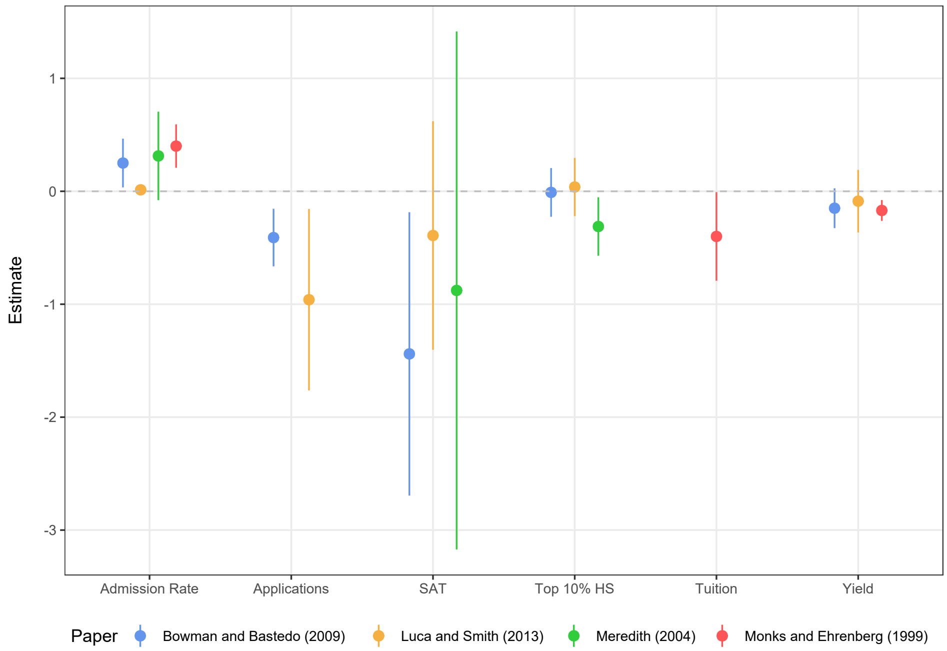

Figure 1: Summary of Estimated Effects from a One Rank Loss in the Literature

aid-adjusted tuition by about 0.4% per loss in rank. Since gross tuition is unaffected in their estimations, Monks and Ehrenberg (1999) conclude that universities raise their aid levels in order to attract applicants to compensate for the loss in popularity.

Figure 1 provides an overview of the size and 95% confidence intervals of the estimates following a one rank decline from these studies. All significant estimates share the same sign and are roughly similar in magnitude. For the paper by Meredith (2004), the figure depicts the estimates from regressions which include only rank movements within the top 25. Analogously, the estimates from Bowman and Bastedo (2009) are those obtained by regressions using the top 25 sample for reasons of consistency. Given that Luca and Smith (2013)'s results are also based on data of the top 25 universities and Monks and Ehrenberg (1999)'s sample contains (almost) exclusively institutions among the top 25, the estimates are comparable. Thus, any remaining differences should be attributable to the considered time period, model specification, or non-differentiation between national universities and liberal arts colleges. The interpretational units of the estimates on the admission rate, the percentage of students from the top 10% of their high school class, and yield are percentage point changes. For the estimates on applications and tuition, they correspond to approximate percent changes due to the log transformation. For the SAT variable, the estimates correspond to point changes on the SAT interval (1-1600).

The effects of a one rank loss unanimously lead to a higher admission rate. These results are consistent with the theory that a lower rank reduces a university's popularity and thereby the number of applications that it receives. The estimates for SAT and the percentage of students from the top 10% of their high school class also have the expected sign. Following a loss in the ranking, universities' students are of slightly lower quality. The results on tuition are sparse, but the hypothesis by Monks and Ehrenberg (1999) that universities lower (aid-adjusted) tuition fees to counter the expected decline in applications is appealing. Lastly, the implications for the yield rate are also in line with expectations. Given that yield is defined as matriculations divided by admissions, yield can be interpreted as a more revised proxy for a university's quality (as seen by students) than the number of applications because the decision to enroll is definite, whereas application decisions are non-binding. However, this interpretation may still be biased by admissions. In this case, yield would measure how future students evaluate a university's fit, conditional on being admitted.

Several other authors have studied U.S. News rankings in terms of their effects on admission choices (Griffith and Rask 2007; Alter and Reback 2014; Sauder and Lancaster 2006) and the methodology behind the rankings (Webster 2001; Gnolek, Falciano, and Kuncl 2014; Volkwein and Sweitzer 2006; Bastedo and Bowman 2010; Brennan, Brodnick, and Pinckley 2008; Grewal, Dearden, and Llilien 2008).

Using survey data from the Colgate Admitted Student Questionnaires (CASQ) from 1995 to 2004, Griffith and Rask (2007) study whether a university's U.S. News rank influences students' matriculation decisions. The institutions to which students applied include mostly national universities and liberal arts colleges from the top 50 of U.S. News rankings. They find that full-pay and aid-receiving students respond significantly to differences in ranks, with a stronger response for full-pay students. Their estimations using a conditional probability model suggest a decrease in the probability of matriculation by roughly 0.17 percentage points for aid-receiving students and a decrease by 0.5 percentage points for full-pay students for every one rank decline among the best ranks. Given the quadratic model specification, this effect becomes weaker at worse ranks.

Alter and Reback (2014) empirically examine whether a university's standing influences applications and the competitiveness of its students as measured by SAT scores and high school class performance. Using data from 1993 to 2008 on 265 selective universities from the Princeton Review and U.S. News rankings, they observe that a rank among the top 25 increases the number of applications and that a better placement in

U.S. News rankings has a positive effect on the competitiveness of the university's next incoming freshman class.

In the context of U.S. law schools, Sauder and Lancaster (2006) study data of U.S. News rankings from 1993 to 2003 and find that a one rank improvement within the top 50 leads to an increase in applications by 18 applications, an increase in yield by 0.17 percentage points, and an increase in the percentage of high-quality applicants by 0.13 percentage points. Further results suggest that a one rank improvement reduces a university's admission rate by 0.2 percentage points and that tuition is unaffected by changes in rank within the top 50.

Due to multicollinearity among the ranking factors, Webster (2001) uses principal component analysis to isolate each factor's relative explanatory power in the U.S. News ranking from 1999. He finds that the average SAT score, graduation rate, and retention rate were stronger determinants of the variation in ranks than was the academic reputation survey, which had, on paper, the highest weight among the factors.

Other publications report the following results: universities cannot gain considerable, short-term rank improvements through targeted policy changes to the ranking factors unless they expend or reallocate excessive amounts of resources (Gnolek, Falciano, and Kuncl 2014). A university's academic reputation—one of the factors used by U.S. News to generate the rankings—is systematically affected by other underlying ranking factors (Volkwein and Sweitzer 2006; Brennan, Brodnick, and Pinckley 2008) and earlier ranking results (Bastedo and Bowman 2010), as well as highly stable over time (Brennan, Brodnick, and Pinckley 2008; Grewal, Dearden, and Llilien 2008). These results further suggest multicollinearity between the ranking factors as well as persistence of the ranks.

3 Background

3.1 The U.S. News and World Report Rankings

In 1983, media company U.S. News & World Report released its first edition of Best National Colleges, intending to provide a comprehensive ranking of U.S. colleges that facilitated comparisons for prospective students. Since then, the ranking has appeared annually and strengthened its influence in higher education and academia. In fact, among its numerous competitors like Forbes, QS, Niche, Times Higher Education, or the Princeton Review, the U.S. News & World Report university rankings are considered the most popular.[5] In earlier editions of the ranking, USN only assigned numerical ranks to the best 50 universities and placed the remaining schools into tiers based on how deans and provosts of peer universities evaluated their academic quality. Over the years, the ranking has been revised in several aspects. First, because more institutions provide their data to USN, current editions include ranks for much more colleges than in earlier years. Second, numerous sub rankings for different fields of study emerged, including rankings of, for example, engineering, law, or medicine. Third, a university's final rank has become an aggregation of several newly introduced measures at the institution level instead of the one-dimensional rank that only revolved around the academic reputation survey.

In the 2021 edition, USN ranked over 1,400 institutions based on 17 factors used to assess an institution's academic quality. Additionally, the institutions are categorized into National Universities, National Liberal Arts Colleges, Regional Universities, and Regional Colleges, and each category receives its own ranking. According to their descriptions, National Universities are research-intensive institutions that offer a wide range of undergraduate, master's, and doctoral programs. On the other hand, National Liberal Arts Colleges are undergraduate-focused and offer primarily arts programs. Regional Universities and Colleges are small undergraduate institutions and offer fewer master's and almost no doctoral programs. While many earlier works focused on heterogeneous effects of these different classifications, I limit this study to a sample of National Universities only.

3.2 The U.S. News Ranking Methodology

The ranking methodology is an essential aspect of this study. As mentioned earlier in this section, in the beginnings of the USN ranking, only the academic reputation survey of administrators from peer universities determined a university's position in the ranking, whereas a growing number of institutional measures were added over the years (and some dropped) to improve on the ranking's credibility and ensure integrity in the higher education sector.

Table 1 provides an overview of the ranking methodology and its development over the years. The quality of a university is measured along six dimensions, where each may be compound of various measures of institutional quality. For the methodology of the 2012 and 2014 rankings, these dimensions are academic reputation, student success, student excellence, faculty resources, faculty instructional spending, and alumni dona-

[5] Cf. Ehrenberg 2003 p. 146

Table 1
U.S. News National University Ranking Methodology

Ranking Factor	Weight		
	2019	2014	2012
Academic Reputation Survey	20%	22.5%	22.5%
Graduation and Retention			
Average Six-Year Graduation Rate	17.6%	18%	16%
Average Six-Year Graduation Rate Performance	8%	7.5%	7.5%
Average First-Year Retention Rate	4.4%	4.5%	4%
Social Return			
Pell Grant Graduation Rate	2.5%	0%	0%
Pell Grant Graduation Rate Performance	2.5%	0%	0%
Faculty Resources of Previous Year			
Class Size Index	8%	8%	8%
Faculty Salary	7%	7%	7%
Percent of Faculty with Teminal Degree	3%	3%	3%
Percent of Faculty Fulltime	1%	1%	1%
Stundent-Teacher Ratio	1%	1%	1%
Student Selectivity of Previous Year			
SAT Score	7.75%	8.125%	7.5%
High School Class in Top 10%	2.25%	3.125%	6%
Admission Rate	0%	1.25%	1.5%
Instructional Resources per Student	10%	10%	10%
Average Alumni Giving Rate	5%	5%	5%

tions. The final score is then calculated depending on how well a university performs in each dimension—weighted based on how much importance U.S. News attaches to each.

The highest weighted factor is the academic reputation survey which accounts for 22.5% of the overall score.[6] In this survey, USN asks presidents and deans of admissions of peer institutions to rate other schools on a rate of 1 (worst) to 5 (best) according to how they evaluate a schools' quality. USN claims that the survey provides insight into factors of academic quality that cannot be easily captured by other variables. However, the results by Volkwein and Sweitzer (2006) and Brennan, Brodnick, and Pinckley (2008) have shown that the survey scores are highly connected to the other ranking factors. The survey may therefore only provide limited additional information on a university's quality.

Student success is made up of the graduation rate (16%), the retention rate (4%),

[6] I take the 2012 weights as a reference as this is the year which is closest to the sample mean.

and a university's graduation rate performance (7.5%). The graduation rate measures the rate of students who completed their degree within 150% of the expected time. Since programs at national universities typically take four years and USN uses a rolling average of the latest four years, this measure amounts to the four-year rolling average of the rate of students who completed a degree within six years. Graduation rate performance measures the deviation of this graduation rate from a university's predicted value. These predictions are estimated using data on admissions, the rate of undergraduates receiving Pell Grants, financial resources, the rate of first-generation students among aid recipients, and whether universities focus on maths or science. Universities that perform better than their estimated value are rewarded a higher score than those failing to meet this benchmark. However, it is unclear to what extent this estimated graduation rate poses a justifiable benchmark for a university's graduation rate, especially because its estimation is largely a black box.[7] The third factor is the four-year average of the retention rate of first-year students, i.e., the rate of freshmen students who were still enrolled the following fall.

Including student selectivity into the ranking formula is motivated by the straightforward view that students who did well in high school tend to cope better with the obstacles that await them in college. A university's student selectivity is therefore measured by the average reading, writing, and mathematics portions of the SAT score of previous years' freshmen (7.5%), the proportion of previous years' freshmen whose grades were in the top 10% of their high school class (6%), and the university's admission rate (1.5%).

Faculty resources describe the human capital endowment of the teaching staff and the learning atmosphere of universities. This dimension contains a university's previous year's class size index (8%), average faculty salary (7%), percentage of faculty with a terminal degree in their field (3%), percentage of faculty members who work full-time (1%), and student-teacher ratio (1%). While smaller class sizes and lower student-teacher ratios make it easier for teachers to address students' personal needs in learning, higher degrees and full-time positions are likely to have a positive impact on instructors' expertise and engagement.

Lastly, faculty spending is measured by the average per-student expenditure on instruction, research, and student services of the last two years. Alumni donations are measured by the average percentage of alumni (with bachelor's degrees) who donated to the university in the last two years.

[7] For a more nuanced (but somewhat outdated) view on this measure, see Porter (1999).

This specific composition of ranking factors leads to a number of questions. For instance, how are these factors justified? Why include these very factors in the ranking formula but not others? What determines a factor's weight? In the following, I briefly address objections that deal with these kinds of questions.

3.3 Criticism

While I do not attempt to validate whether the rankings presented here are a proper reflection of a university's actual quality, many studies did so in recent years—and the prevailing opinion appears to be that they are not. The USN rankings have received plenty of criticism, which can be categorized into three main points.

Drawing upon the initial sentence, the first main point of criticism is that the rankings do not adequately measure a university's quality. A common point is that the surveys where college administrators are asked to evaluate peer universities mainly serve a subjective popularity contest instead of an unbiased evaluation of their quality. Since many college administrators are highly connected to other institutions, universities with a better network tend to have a better repuation and minor flaws are more likely to be overlooked. Another point is that important aspects like teaching quality are not taken into account by the factors and that universities have different goals such that no single methodology can reliably assess the quality for all universities alike—although the distinction between national universities, liberal arts colleges, and regional institutions addresses this argument.[8] Similarly, the ranking's focus on university endowment and student ability favors the wealthy and selective universities but discriminates against public institutions because they tend to admit a higher percentage of students and have longer average graduation rates. Therefore, no single ranking methodology should be used to evaluate a heterogeneous ensemble of universities.[9]

The second main point of criticism is that the ranking formula incentives universities to manipulate the values for the different ranking criteria to receive a more favorable rating. Given that USN asks universities to send them their admission data, there is the chance that the data provided by college administrators are simply wrong or deliberately altered. Examples of this include tampered SAT or graduation rate data.[10] Other methods in which universities found ways to misrepresent their data are known. In this case, universities do not directly report false data but adjust parts of their

[8]Cf. Altbach (2006) p. 2.

[9]Cf. Machung (1998) p. 13 and Myers and Robe (2009) p. 23.

[10]Cf. Machung (1998) p. 14.

admission procedure or internal data documentation such that the data is indirectly polished. For example, universities artificially alter their application processes to receive more applications and thus appear more selective, or they do not admit applicants they believe are overqualified and will eventually enroll at another university.[11]

The third point of criticism is about the ranking factor weights and their fairly common readjustments over time. The view of what makes a good university should be relatively constant over time—the weights of the underlying criteria (or entire criteria for that matter), however, have changed numerous times. Assuming that underlying university characteristics did not change, would the resulting ranking differences thus indicate that the quality of universities changed? The answer seems to be no. Changes to the weights are primarily means to make the rankings fluctuate from year to year because hardly anyone would buy the magazine's issue if universities always ended up on the same rank. Thus, adjustments to the weights produce "the news that sells the magazine".[12] In fact, it is often criticized that large fractions of the yearly ranking differences can be attributed to changes in the ranking methodology instead of changes in actual quality. Hence, most of the variation in the yearly rankings is effectively the result of methodology changes.[13]

4 Data

My data draws from two sources. First, the information on university rankings draws from past editions of the U.S. News and World Report Best National University Rankings. Second, I have data on a range of additional characteristics at the university level, which I collected from the Integrated Postsecondary Education Data System (IPEDS).

4.1 U.S. News Rankings

The ranking variable includes the ranks of the top 125 universities from the 2008-2015 editions of the USN Best National University Rankings. Since the top 125 here means the 125 highest ranked universities as per the 2008 ranking, some universities may have ranks worse than 125 in other years. Of these 125 universities, I drop seven due to data availability constraints so that my final data panel includes 118 universities.

[11]Cf. Machung (1998) pp. 14–15 and Hossler (2000) pp. 21–22.

[12]Machung (1998) p. 15.

[13]Cf. Dichev (2001) p. 262 and Myers and Robe (2009) p. 23.

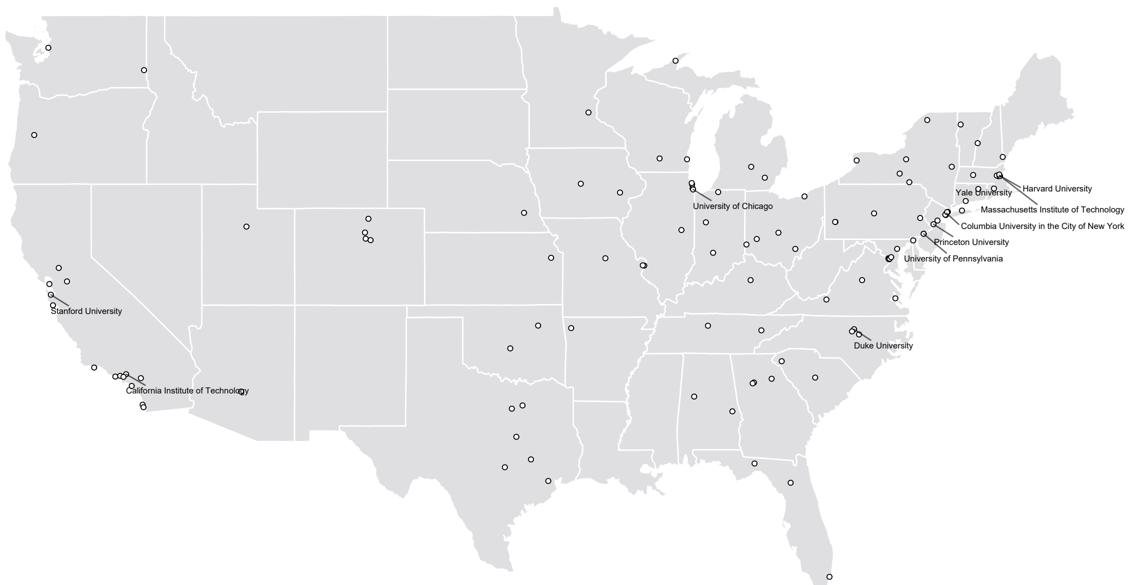

Figure 2: Locations of Sample Universities in the United States

Figure 2 shows where the universities are located within the United States. The vast majority are in the East, some in the West, and only a few in the Midwest. Western universities are primarily located in California, which has the most universities in the sample (14), followed by New York (11) and Massachusetts (8). The highlighted universities are those with an average rank in the sample period below 10. Strikingly, they are predominantly located in states which used to be British colonies—probably because these universities were founded much earlier than others and were able to establish their institutional quality over the years.

My sample is specific in a few ways. First, recalling the distinctions made by USN, the universities are exclusively categorized as National Universities, which are research-intensive and offer doctoral, master, and undergraduate programs alike. Second, these universities are among the best in the country and may therefore provide a contrast to significantly lower ranked universities. Third, as a natural consequence of the rankings, all universities are located within the United States. Thus, the results in this study do not generalize to environments where the setting is fundamentally different, e.g., ranking effects of regional institutions/liberal arts colleges, universities of overall poorer quality, or rankings of universities in other countries.

4.2 University Characteristics

The information on university characteristics comes from the Integrated Postsecondary Education Data System (IPEDS), which is a data collection branch of the U.S. National Center for Education Statistics (NCES). The NCES, in turn, is subordinate to the U.S. Department of Education and is dedicated to collect, report, and analyze data related to education within the United States. I have data on 23 variables at the university level, including unique IPEDS codes, which makes it possible to connect university data to the ranking data.

I analyze the effects of rankings on seven dependent variables—the average SAT, the number of applications, admissions, and enrollments, as well as the admission rate, yield rate, and tuition. The average SAT is the average SAT score of students from a given university. Unlike earlier publications that focus on the average SAT score of the incoming freshmen class, I study ranking effects on the average score at the entire university. Earlier works also frequently use the admission and yield rate as dependent variables, which I do similarly. However, having access to the number of applications, admissions, and enrollments allows me to break down effects on these rates that may be driven by the numerator or the denominator. Tuition covers the average in-state tuition and fees published by the university.

The set of independent variables cover the USN rank and other university characteristics. Specifically, the variables include six of the 14 ranking factors (or close approximations thereof), which are part of the USN ranking methodology. I have data on the graduation and retention rate, the average faculty salary, the percentage of faculty that is full-time, the student-teacher ratio, and the instructional expenditure per student. Two additional factors, the average SAT score and the admission rate, are already part of the dependent variables. Unlike the ranking methodology, I do not use averages from past years, e.g., for the graduation or retention rate, as this would only take away valuable variation, which, in most cases, is already very low. Alongside these variables, my data also contains a binary variable for whether a university is publically or privately controlled, the total cost of attending a university, which includes in-state tuition and fees, books and supplies, on-campus room and board, and other on-campus expenses, the 75 percentile of the Math and Reading SAT distribution, the number of first-time, degree-seeking undergraduates, and the number of total students.

Table 2
Descriptive Statistics

	Mean	Std. Dev.	Min.	Max.	No. Obs.
A. Dependent Variables					
Average SAT	1268	112	1028	1555	1298
Applications	23163	13145	1558	97112	1298
Admissions	10522	6654	553	36088	1298
Enrollments	3290	2009	214	9488	1298
Admission Rate	0.49	0.23	0.048	0.93	1298
Yield Rate	0.35	0.15	0.081	0.84	1298
Tuition	23550	15450	3206	55056	1298
B. Independent Variables					
Rank	62	37	1	145	944
Private	0.47	0.5	0	1	1298
Graduation Rate	0.79	0.1	0.56	0.98	1298
Retention Rate	0.91	0.051	0.72	1	1298
Avg. Faculty Salary	10728	2192	5629	22146	1298
Faculty Fulltime	0.77	0.14	0.38	1	1298
Instructional Expenditure	21777	19109	6089	118787	1298
Total Cost	38089	16638	13980	72717	1298
Student-Faculty Ratio	14	4.6	3	27	1062
Math SAT (75%)	699	54	570	800	1169
Reading SAT (75%)	673	55	560	800	1169
Undergraduates	3343	2062	214	10835	1298
Students Total	20057	11690	2086	59735	1298

Notes: This table provides basic descriptive statistics pooled over cross-section ($n = 118$) and time dimension ($t = 2006, ..., 2016$). Private is a binary variable and captures the control of a university: 1 for private, 0 for public. Instructional expenditure covers the average instructional expenditures made by the university per student. Yield rate equals the proportion of admitted students that enrolled at the university, i.e., equals enrollments divided by admissions. Tuition covers the average in-state tuition and fees published by the university. Total cost sums up the average cost of attendance. It includes in-state tuition and fees, books and supplies, on-campus room and board, and other on-campus expenses. Math and Reading SAT measure the 75% percentile of the respective portions of the SAT score of students. Undergraduates is the number of first-time, degree-seeking undergraduate students and Students Total is the total number of enrolled students.

4.3 Descriptive Statistics

Table 2 provides basic summary statistics pooled over universities and time. In total, the rank variable has 944 observations, as there are 118 observations for each of the eight years (2008–2015) in the data set. Since I also plan to model the ranking effect by

Table 3

Descriptive Statistics of Dependent Variables by Control and Size

	Overall	Control		Size		
		Public	Private	Small	Medium	Large
Average SAT Score						
Mean (SD)	1268 (112)	1208 (73)	1334 (111)	1340 (115)	1232 (97)	1216 (61)
Min., Max.	[1028, 1555]	[1028, 1422]	[1050, 1555]	[1050, 1555]	[1028, 1481]	[1052, 1386]
Applications						
Mean (SD)	23163 (13145)	25861 (13874)	20177 (11586)	15933 (9123)	26323 (14410)	29159 (10495)
Min., Max.	[1558, 97112]	[3215, 97112]	[1558, 60724]	[1558, 44816]	[7993, 97112]	[9101, 68553]
Admissions						
Mean (SD)	10522 (6654)	14299 (5593)	6340 (5039)	4414 (2941)	12670 (5466)	16657 (4881)
Min., Max.	[553, 36088]	[2556, 31630]	[553, 36088]	[553, 20366]	[3492, 36088]	[6827, 29878]
Enrollments						
Mean (SD)	3290 (2009)	4660 (1673)	1773 (1010)	1270 (411)	3605 (1005)	6126 (1268)
Min., Max.	[214, 9488]	[787, 9488]	[214, 6082]	[214, 2229]	[1530, 7541]	[2418, 9488]
Admission Rate						
Mean (SD)	0.49 (0.23)	0.61 (0.17)	0.36 (0.21)	0.36 (0.22)	0.54 (0.21)	0.61 (0.15)
Min., Max.	[0.048, 0.93]	[0.16, 0.93]	[0.048, 0.91]	[0.048, 0.85]	[0.094, 0.93]	[0.22, 0.92]
Yield Rate						
Mean (SD)	0.35 (0.15)	0.35 (0.11)	0.36 (0.18)	0.36 (0.18)	0.32 (0.13)	0.39 (0.1)
Min., Max.	[0.081, 0.84]	[0.13, 0.71]	[0.081, 0.84]	[0.093, 0.84]	[0.081, 0.79]	[0.14, 0.79]
Tuition						
Mean (SD)	23550 (15450)	10068 (3080)	38476 (8259)	37228 (9451)	18617 (14059)	10067 (5135)
Min., Max.	[3206, 55056]	[3206, 22997]	[3620, 55056]	[8490, 55056]	[4080, 52283]	[3206, 43204]

Notes: Public and private have 682 and 616 university-year observations, respectively. Small, medium, and large have 469, 557, and 272 university-year observations. The size categories are defined by the number of undergraduate students at the university: $[0, 2000]$ *for small,* $(2000, 5000]$ *for medium,* $(5000, \inf]$ *for large.*

lagged values and ranking factors from up to two previous years could potentially bias the estimation, my data also contains observations of most university characteristics for 2006, 2007, and 2016. Exceptions to this are the student-teacher ratio, for which I do not have data from 2006 and 2007, and the Math and Reading SAT variable, which are missing entirely for 2016 and sporadically in other years (11 university-year observations).

Related studies often emphasize the effect heterogeneity between private and public or small and large universities. To provide a better understanding of how the data varies between these groups, Table 3 shows summary statistics of the dependent variables. Unsurprisingly, private institutions have much higher tuition fees and admit significantly fewer applicants while receiving only slightly fewer applications. This higher selectivity then results in more qualified students as measured by the average SAT at the institution. For size, a university is classified as small if it has fewer than 2000 undergraduate students, medium if it has between 2000 and 5000, and large if it has more than 5000.

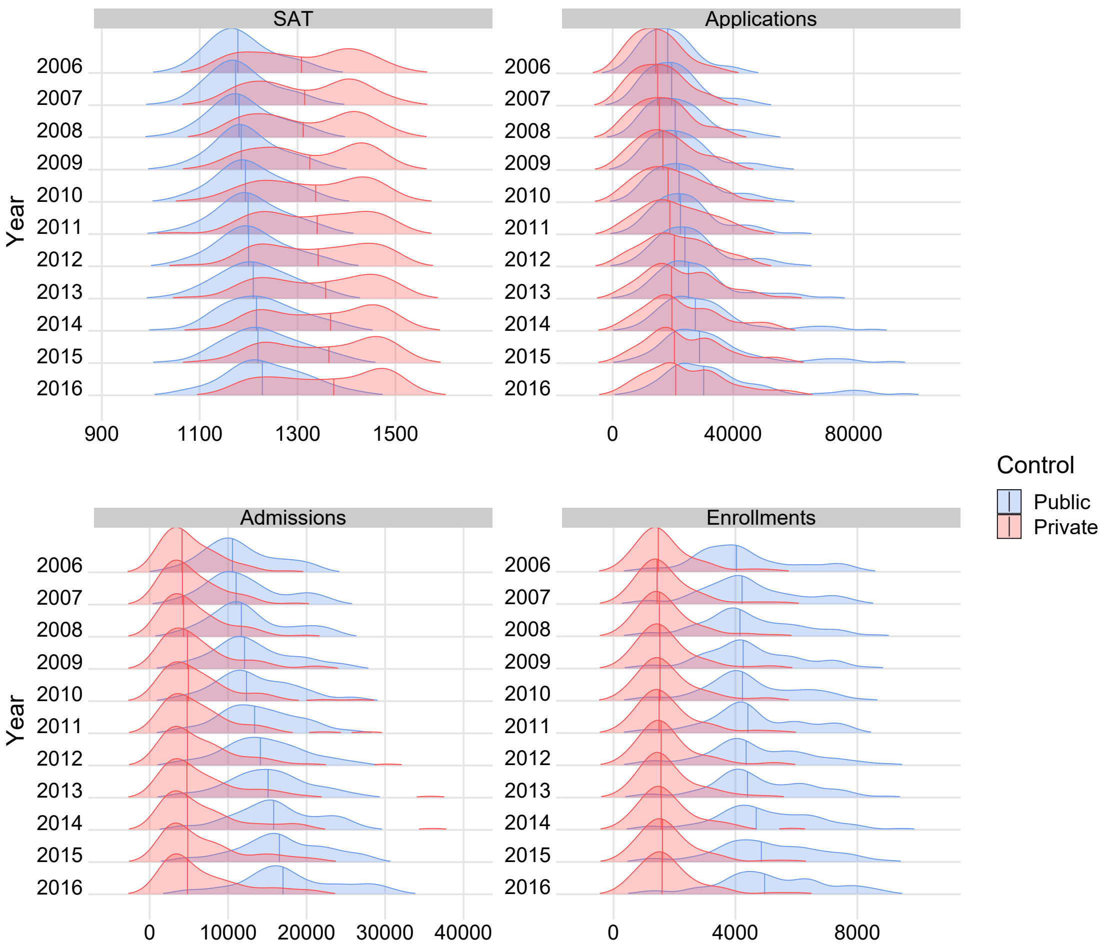

Figure 3: Trends of Dependent Variable Distributions (1)

There is a large intersection between the small and private universities—around 93% of small universities are private. Of the universities classified as medium, 30% are private, whereas only about 4% of the large universities are private. Due to this, the statistics of small universities are similar to private universities but significantly different from universities classified as medium or large.

For the econometric analysis, it is important to identify trends in the data. Figure 3 and Figure 4 depict trends of the dependent variable distributions to get a good understanding of how they change over time. The graphs show the distributions separately for public and private universities as well as the median in each year. Over the sample years, the average SAT score at universities increased for both public and private universities, as shown by the shift in the distribution to the right. Applications develop

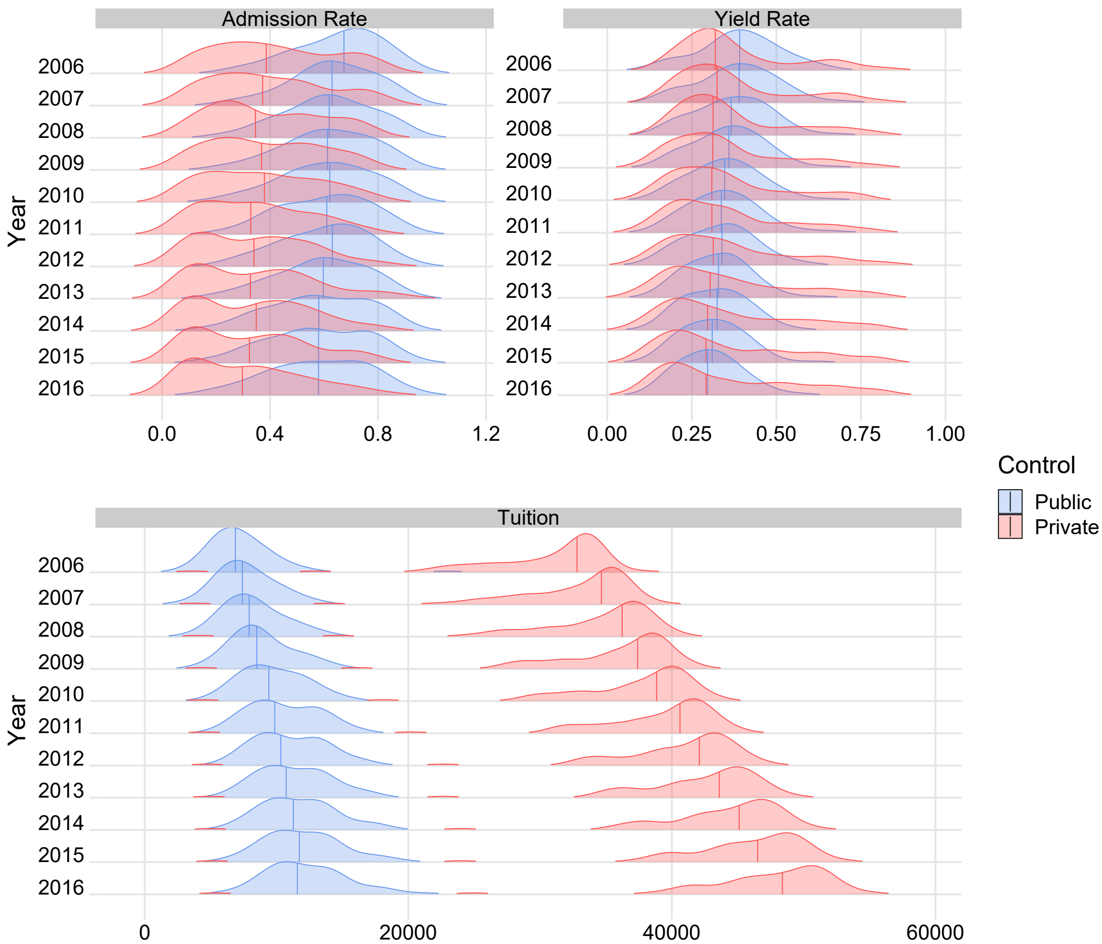

Figure 4: Trends of Dependent Variable Distributions (2)

all in all very similarly, although the pronounced tails of the distributions indicate that few universities receive increasingly more applications than the rest. A simple metric that captures this nonnormality may be the difference between the mean and median in the sample. Indeed, in 2006, this difference was below 600, while it was over 4000 in 2016. In terms of the number of admissions and enrollments, the data look similar. In both cases, only publically controlled universities appear to see shifts towards the right. The admission rate distributions do not change much, as shown by the median shifting marginally towards lower values. Following the developments from admissions and enrollments, the median yield rates of public and private universities seem to align over the years. However, there are few outliers with significantly higher yield rates, especially among private universities. Lastly, tuition fees of private universities increased

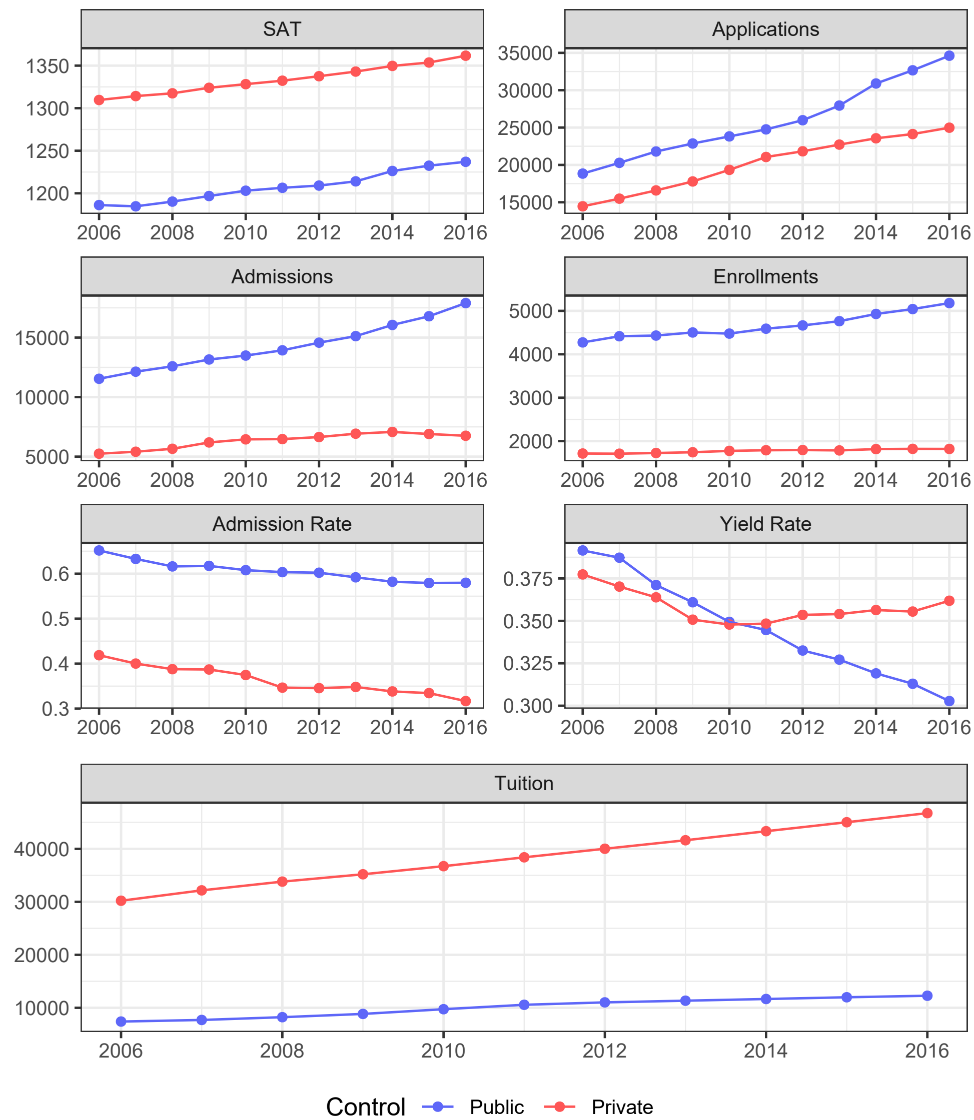

Figure 5: Trends of Dependent Variable Means

consistently in the timeframe, whereas tuition fee growth of public universities flattened in more recent years.

Figure 5 provides an additional complement to the distributional trends by showing the mean values of the dependent variables instead of the median over time. For most variables, the graphs mostly mirror the above findings, although the trend of the private yield rate does differ slightly. Here, since the probability mass in the right tails of the distribution has increased more than the mode has shifted to the left in recent years, the mean curve, albeit marginally, goes upward rather than downward.

Table 4
Correlations of Ranking Factors and Ranks

	Rank	SAT	Grad.	Ret.	Sal.	FT	Inst.	SFR	Adm.
Rank	1.00	−0.86	−0.92	−0.88	−0.71	−0.11	−0.65	0.60	0.81
SAT	−0.86	1.00	0.83	0.82	0.74	0.07	0.73	−0.72	−0.88
Graduation Rate	−0.92	0.83	1.00	0.90	0.70	0.07	0.61	−0.58	−0.80
Retention Rate	−0.88	0.82	0.90	1.00	0.69	0.14	0.57	−0.51	−0.81
Faculty Salary	−0.71	0.74	0.70	0.69	1.00	0.08	0.68	−0.54	−0.75
Faculty Fulltime	−0.11	0.07	0.07	0.14	0.08	1.00	0.05	0.07	−0.04
Instr. Expenditure	−0.65	0.73	0.61	0.57	0.68	0.05	1.00	−0.68	−0.67
Stud.-Fac. Ratio	0.60	−0.72	−0.58	−0.51	−0.54	0.07	−0.68	1.00	0.66
Admission Rate	0.81	−0.88	−0.80	−0.81	−0.75	−0.04	−0.67	0.66	1.00

As a key independent variable, ranks are of particular interest in this study. Like previous authors who have found multicollinearity within ranking factors, I discuss how factors correlate with each other and with the ranks. I also address the variability of rankings within universities and find which universities rise or fall the most in the rankings over the observed period.

Table 4 illustrates the correlations between the ranking factors and the rank. Since the various factors are criteria that determine a university's overall rank according to the USN ranking methodology, a fairly high correlation is to be expected. The graduation rate, retention rate, average SAT score, and admission rate all have absolute correlation coefficients above 0.8. Other factors are also moderately correlated with ranks, the only exception being the percentage of faculty who are full-time. In addition, it is noticeable that the ranking factors are also highly correlated with each other. For example, reconstructing the rankings using only graduation rate information would likely give a good approximation of the USN rankings. This may also be true for other ranking factors for which I do not have data, since it seems plausible that, for example, universities with a higher percentage of students from the top 10% of their high school class or with smaller class sizes on average would also have higher graduation rates. At first glance, this is evidence that most of the ranking criteria capture essentially the same information.

In the next paragraph, the variation of the rankings is examined due to the possible complications it can cause with the econometric approach. Specifically, this may play a role in fixed-effects models, which essentially look at what drives the variation of

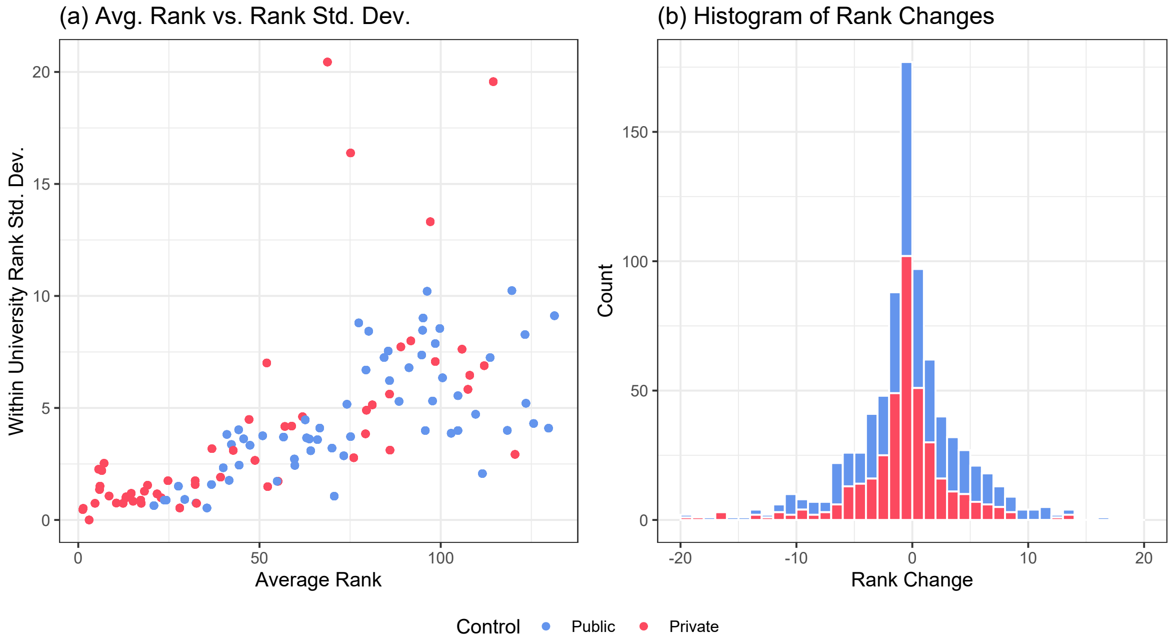

Figure 6: Ranking Variability

Notes: Plot (a) depicts for each university in the sample the average rank and the standard deviation of its ranks. Plot (b) shows rank changes for all universities and all years. Rank changes are defined as the difference between current and previous years' ranks. Since ranking data is available for eight years (2008-2015), this includes 826 observations.

variables within universities. Therefore, the observations presented here give an initial idea of what may compromise the validity of later results.

Figure 6 (a) plots the average rank of the 118 universities against their respective rank standard deviations. On average, the within university variation of ranks increases with a higher average rank. The probability that a university ends up far away from its current rank in the standings in the following year is much smaller for a top-ranked university than for a poorly-ranked university. Plot (b) of Figure 6 shows how many ranks the universities in the sample gained or lost from one year to the next. Here, negative values indicate gains, and positive values indicate losses. A little over 50% of all rank changes over the years are either by one or two places. As expected, significantly greater rank changes were rare due to only slight adjustments to factor weights and the assumption that large changes to a university's quality would usually take more than a year to come into effect. Figure B1 additionally breaks down the rank changes over the years. Using the graphs, one may find out which group of universities benefited most in which year and also which year caused the most fluctuations in the standings. For

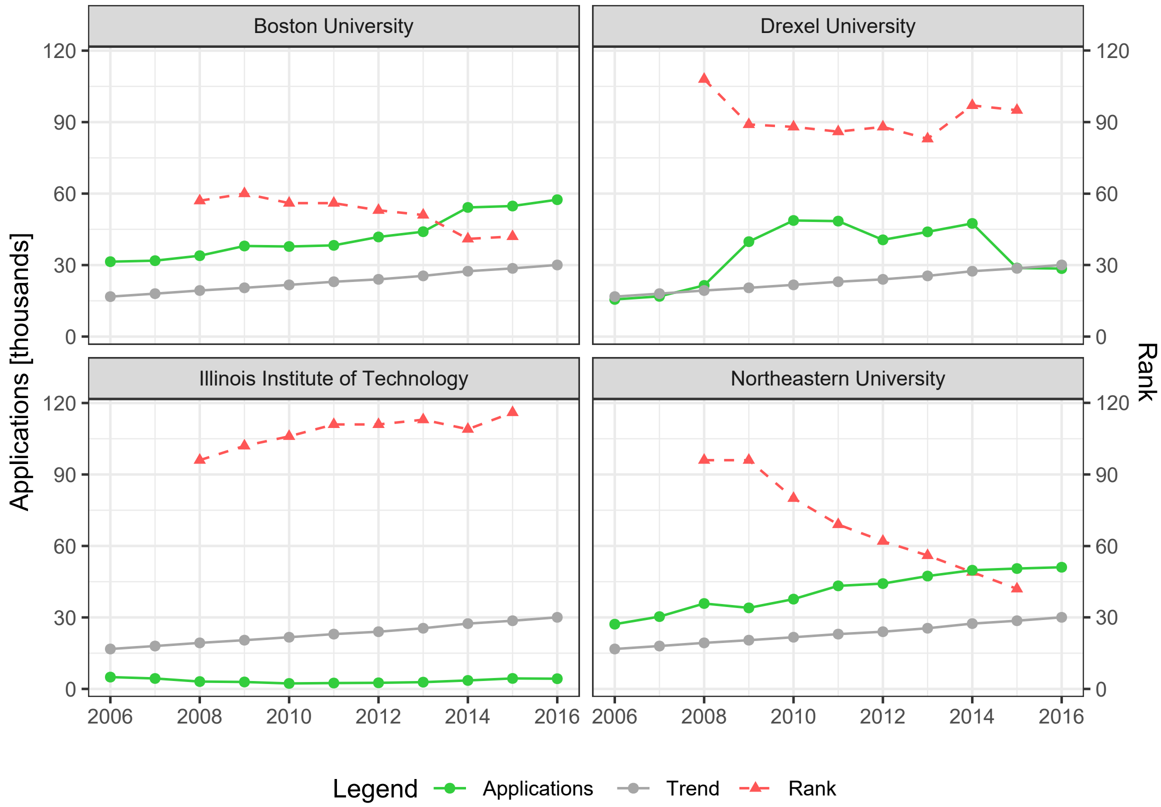

Figure 7: Relation of Applications and Ranks of Selected Universities

instance, as the tails of the 2013 distribution show, public universities can be considered losers and private universities winners that year. On a related note, Figure B2 shows how the universities' ranks relate to the ranks from one year before and four years before. It is worth noting that in 2012 and 2014, there were changes to the ranking methodology. Thus, even in these years, there were only minor changes in the rankings, confirming the finding that the variation in the rankings is small.

In this final paragraph, I examine specific cases of universities that may provide prima facie evidence that placement in the USN rankings matters. Thus, in addition to the consensus in the literature on the importance of USN rankings, the presented graphs may provide further motivation for the empirical analysis. Figure 7 shows the evolution of rankings and applications of four universities over the years. For graphical convenience, the number of applications is measured in thousands, and each graph also shows the trend of the average applications that the universities received. Moreover, all four universities are private. In all four graphs, the rank and application curves move adversely to each other. When a university moved up in the rankings (downward movement of the curve), more students tended to apply to that university. And vice versa, when a university fell in the rankings, then it could not attract as many applicants. This pattern is fairly stable for these four universities—for example, the application and rank curves of Boston and Drexel University look almost as if they mirror each other horizontally. Still, the increasing number of applicants may simply be due to the general underlying trend in applications, so the applications Boston or Northeastern University received could be entirely unrelated to their ranking placements. Hence, the examples of Drexel University or the Illinois Institute of Technology, whose applications did not follow the overall trend, might make a stronger case for a meaningful ranking effect.

5 Empirical Strategy

5.1 Baseline Effect

For the baseline ranking effect, I model each admission variable as a function of a university's previous year's placement in the USN ranking, a set of university-specific and year effects, and additional university characteristics. I adopt the approach to use the lagged rank as it is commonly done in the literature. However, I also estimate regressions where the ranking effect is more flexibly modeled with respect to the timing of the effect. After all, the reaction to the ranking may come into effect only after a certain amount of time. Therefore, for the baseline effect, I estimate variations of the following equation:

$$Y_{it} = \beta_0 + \beta_1 \text{Rank}_{i,t-1} + \delta X_{it} + c_i + s_t + u_{it}, \tag{1}$$

where Y_{it} is one of the dependent variables for university i measured in year t, X_{it} is a set of time-varying university characteristics controlling for possible omitted factors, c_i captures unobserved time-constant university-specific effects, s_t captures year effects common to all universities (i.e. the common trend), and u_{it} is a mean zero error term. In this estimation setup, interest lies on β_1, the effect on admission outcomes induced by changes in a university's USN rank. Using this setup with university and year fixed effects, I am essentially looking at whether deviations of a university's rank from individual and time period means lead to systematic deviations from the mean of a university's admission outcomes.

There are three potential threats to identification in this estimation setup. First, and perhaps most likely, the obtained parameter estimates for the ranking effect are biased if there are omitted variables that cause the regressor of interest to be correlated with the error term. This is presumably true for the ranking factors, as they likely affect the admissions outcomes and also determine, albeit with varying weights, what ranking a college ultimately managed to achieve. To reduce this bias, I include the ranking factors on which data was available as control variables. I have data on the graduation rate, retention rate, average SAT score, admission rate, average faculty salary, the percentage of faculty that is full-time, the instructional expenditures per student, and the student-faculty ratio. Together their weights make up roughly 50% of the total ranking methodology weights. Arguably, this is not a lot, however as mentioned earlier, the ranking factors used by USN are highly correlated. It is likely that factors for which I have no data are also strongly correlated, e.g., it seems plausible that class size is strongly related to the graduation rate or the student-faculty ratio. Similarly, one would expect a strong relationship between the percentage of students who graduated top 10% of their high school class and the average SAT score or the graduation rate. Besides these ranking factors, the academic reputation survey accounts for the highest weight but is also missing in my data sample. The same logic may apply here as earlier works found that the graduation rate, the retention rate, and the average SAT score at a university (and other ranking factors) are strongly associated with the survey's outcome. Therefore, missing this information may not be as problematic because the available ranking factors capture mostly the same information. It might also be the case that, given its inherent consistency, university reputation is accounted for by the university fixed effects in the regression equation since their inclusion makes the model robust to unobserved but constant effects specific to each university.

A great advantage that comes with the information on USN's ranking methodology is that it allows me to quantify the bias in the ranking effect estimate if the ranking factors were omitted from the regression equation. The idea here is that since the USN ranking factors determine a university's placement in the ranking, the bias reduction from using these factors as control variables should be proportional to how well a regression of rank on the set of ranking factors can predict the ranks. Since it is clear that every available ranking factor plays a role in the construction of the ranking, all of them would likely improve on the fit of such a model (although to different degrees due to each factor's weight). However, the motivation to thin out the set of ranking criteria is because of the substantial multicollinearity between them. Although strictly, only perfect multicollinearity would be problematic from a statistical viewpoint because the model would not be identified, a high correlation between the independent variables still compromises the ability to interpret model parameters. E.g., in typical policy

Table 5
Regressions of Rank on Ranking Factors

	(1)	(2)	(3)	(4)	(5)	(6)
Graduation_{t-2}	-316.012^{***}	-195.797^{***}	-179.046^{***}	-175.570^{***}	-185.063^{***}	-185.274^{***}
	(8.859)	(22.532)	(21.079)	(20.800)	(25.125)	(25.154)
Retention_{t-2}		-276.917^{***}	-257.721^{***}	-245.259^{***}	-220.687^{***}	-218.053^{***}
		(52.397)	(51.218)	(49.429)	(59.022)	(59.104)
Instruction_{t-2}			-0.246^{***}	-0.204^{***}	-0.131^{*}	-0.126^{*}
			(0.057)	(0.058)	(0.067)	(0.068)
Fac. Salary_{t-2}				-1.090^{*}	-1.571^{**}	-1.561^{**}
				(0.610)	(0.670)	(0.668)
S.F.–Ratio_{t-2}					0.391	0.427
					(0.321)	(0.341)
$\text{Fac. Fulltime}_{t-2}$						-4.413
						(7.687)
Observations	708	708	708	708	532	532
Adjusted R^2	0.841	0.870	0.879	0.880	0.890	0.890
Test MAE	11.238	10.497	9.884	9.821	8.955	8.919

Notes: Each model in columns (1)–(6) includes an additional intercept and no fixed effects. Regressors are stepwise selected via the minimized sum of squared residuals condition. Heteroskedasticity-robust standard errors clustered by university in parentheses. The models are fitted on a random 75%-subset of the original 944 university-year observations. The mean absolute error is calculated on the remaining 25% of observations, differences in model diagnostics were however negligible.

evaluation studies, researchers are interested in the causal effect a policy had on a certain variable. But the effect of a change in ranks on the admission outcomes is quantified ceteris paribus, an assumption that is hardly warranted when covariates are highly correlated. This is essentially a trade-off: a model with minimal bias but losses in interpretability on the one side or a model with better interpretability but potentially biased estimates on the other.

To resolve this trade-off, I choose a subset of the ranking criteria that has a lower correlation among its variables while still capturing a large proportion of the variation in ranks. To this end, I use a subset selection algorithm that identifies among all possible regressors the set of regressors that minimize the sum of squared residuals. Each of these models is summarized in Table 5. Since USN's rankings are built upon information from averages of previous academic years, the ranking factors are lagged by two years to approximate the ranking construction most adequately without losing observations in the sample. Using one-year lags of the controls would not be sufficient because USN effectively publishes the rankings one year ahead, i.e., the 2015 edition of Best National University Rankings appears in the fall of 2014 and is based upon data from before

2014. And since the majority of variables in the data sample are measured in academic year intervals, information from the academic year 2014/15 could not have impacted the 2015 edition of USN ranks simply because it was not available.[14] Moreover, I exclude both the average SAT score and the admission rate from the set of possible regressors because they are primarily modeled as dependent variables in this study—introducing them on the left-hand side would likely cause interference between the autoregressive part and the time fixed effects. To be consistent across model specifications, I also exclude them in models for the other admission outcomes. The model specifications have slightly fewer than the 944 available university-year observations due to a split into a train (75%) and test data sample (25%). The number of observations in specifications (5) and (6) is again lower because they include the student-faculty ratio, for which data was not available in 2006 and 2007.

Each column in Table 5 shows the model with $k = \{1, \ldots, 6\}$ predictors that minimize the sum of squared rank residuals. That is, column (2) is the model with minimal RSS out of all possible 2-predictors models, column (3) is the model with minimal RSS out of all 3-predictor models, and so forth. The single most influential ranking factor that best explains the variation in ranks is the graduation rate. This may not be so surprising given the very high correlation between them (0.92), however, it is still remarkable that just with this variable alone, a university's placements in USN rankings can be somewhat closely predicted with an average absolute error of 11 places. Ultimately, I chose specification (3) including the graduation rate, the retention rate, and the instructional expenditure per student as the best compromise for the bias-interpretability trade-off, as additional ranking criteria do not seem to offer much benefit in terms of an increased explained variance or a lower mean absolute error of prediction. In fact, both metrics appear to stagnate when adding more than these three factors as predictors. In proceeding estimation tables, specifications that use this confined set of ranking factors will thus be presented alongside specifications that use the entire set of ranking factors.

A second central point for identifying the causal effect is the underlying timing. The literature assumes that the reaction to the rankings takes one year to come into effect, which is a reasonable assumption since universities gather data on the admission outcomes over the course of the academic year and report it when the year ends. To further illustrate the hypothesized causal effect of ranks on the admission outcomes, I assume that students use the most recent USN rankings to make an informed choice of where to apply. That is, when a new USN ranking edition gets released in the fall

[14] The academic year in the U.S. typically starts in September.

of a given year, students browse for information on universities that fit them best and apply relatively more to universities that place better in USN rankings. Therefore, universities' applicant pools and thus their admission outcomes reported in the next year are impacted by their placement in the ranking. However, it is also possible that admission outcomes are affected by rank placements from earlier editions. For example, when deciding where to apply or enroll, a student may find it more convincing to look at how universities placed in farther back years or whether a university's quality is currently on an upward or downward trend. To this end, I also estimate equations that model the timing of the effect in a flexible manner, i.e., equations of the following form:

$$Y_{it} = \beta_0 + \sum_{s=1}^{k} \beta_s \text{Rank}_{i,t-s} + \delta X_{it} + c_i + s_t + u_{it}, \tag{2}$$

where the parameter k determines how far back I look at whether past ranks affect admission outcomes. Note that when $k = 1$, the above equation equals the estimation equation for the baseline effect. Since the effect for farther back rankings is presumably much weaker than for recent rankings, I estimate the above equation for values of $k = \{1, 2, 3\}$.

A third possible threat to identification is reverse causality. When the admission outcomes simultaneously affect the ranking variable, the estimates suffer from a bias. However, this bias potential is only justified for the average SAT score and the admission rate as the dependent variables, given that they are part of the ranking formula. The other admission outcomes are not part of the ranking formula and can therefore not affect the rankings. Nevertheless, I think there are no reasons to believe that reverse causality introduces considerable bias into the parameter estimates. First, the models relate *lagged* ranking placements to the admission outcomes. Therefore, it seems pointless to assume that admission outcomes affect the ranks since the ranking cannot be influenced by an outcome that has not happened at the point of its construction. Second, the weights with which SAT scores and admission rates enter the ranking formula are too small to have a strong impact on the estimates. The SAT average accounts for about 8% and the admission rate for only about 1.5% of the total ranking weights. Moreover, the SAT score in my sample is measured as the average score of the institution, whereas the ranking formula uses the average SAT score of students enrolled in the previous year. Therefore, their impact on estimates is likely to be so small that an econometric approach to solving reverse causality is not necessary.

My hypotheses regarding the ranking effect for each of the dependent variables can be summarized as follows. I keep the ranking variable unaltered, meaning that

I do not reverse-code it, so the estimates are interpreted as the expected effects of a one-rank decrease. For the average SAT score, I expect the estimates to be negative because students, who I assume form realistic expectations about which universities are most likely to accept them, tend to apply where the quality of the student body is most similar to their own (as measured by the SAT). Therefore, when a university drops in the ranking, its perceived quality decreases, lower-level students apply, and thus its applicant pool deteriorates. A similar but straightforward sketched mechanism may apply to the number of applications a university receives. The hypothesis is that a drop in ranks makes a university less attractive to applicants so that it receives fewer applications, on average. Therefore, I expect $\beta < 0$. Regarding the number of admissions, the expected effect of a rank drop is zero as universities probably have an upper limit of students that can be admitted, i.e., they would admit the same number of students irrespective of where they place in the ranking. From this follows that the expected sign of the estimate for the admission rate is positive due to the definition as the fraction of admission and applications. Since the number of enrollments likely approximate how applicants perceive the quality of a university, I hypothesize that applicants, on average, are more likely to enroll at better-ranked universities, therefore $\beta < 0$. In conjunction with the presumed effect on admissions, this inevitably means that the estimate of a one-rank drop on the yield rate would be negative. As for the effect of a rank loss on tuition fees, I expect them to be unaffected by changes to a university's USN rank as Section 4 revealed that tuition over the years evolved in an almost static pattern. However, the trends were different between public and private institutions, so there may be heterogeneous effects, which I look at in separate regressions—hence, for the baseline effect, I expect $\beta = 0$.

I examine the heterogeneity of the effect in a proceeding analysis. I do this along three dimensions. First, since the descriptive part showed substantial differences between public and private institutions, I estimate regressions similar to equation (1) but with the ranking effect interacted with an indicator variable for whether a university is privately or publically controlled:

$$Y_{it} = \beta_0 + \beta_1 \text{Rank}_{i,t-1} + \beta_2 \left(\text{Private}_i \times \text{Rank}_{i,t-1}\right) + \delta X_{it} + c_i + s_t + u_{it}. \tag{3}$$

This equation allows me to check whether rank movements induce different effects on the admission outcomes for public or private universities. I believe that, when estimating this equation, it is hard to infer whether it is the differentiation between public and private that causes these estimates or perhaps the differentiation between small and large universities, given that the overlap between small and private universities was quite large.

Size (as measured by the number of students) is the second dimension along which the estimates could potentially differ. Here, I proceed similarly as in Section 4, that is, I create indicator variables for the number of undergraduate students at a given university and interact these with the ranking variable. The three resulting indicator variables are small, medium, and large: a university is small if it has less than 2000 undergraduate students, medium if it has between 2000 and 5000, and large if it has more than 5000 undergraduate students. Therefore, these regressions have the form

$$Y_{it} = \beta_0 + \beta_1 \text{Rank}_{i,t-1} + \beta_2^l \left(S_l \times \text{Rank}_{i,t-1}\right) + \delta X_{it} + c_i + s_t + u_{it}, \tag{4}$$

where S_l are the previously mentioned indicator variables which are one if university i is of size $l = \{\text{Medium}, \text{Large}\}$.

The third dimension along which the ranking estimate could be heterogenous is the ranking placement itself. Earlier sections revealed that there is significantly less variation among the best ranking placements, which could indicate that movements within these good positions are much more infrequent and therefore more valuable for a university than movements within poorer ranks. Hence, dropping a rank in the top ranking placements could have a stronger effect on the outcomes than dropping a rank in relatively worse ranking placements. I test this hypothesis with the following equation:

$$Y_{it} = \beta_0 + \beta_1 \text{Rank}_{i,t-1} + \beta_2^j \left(B_j \times \text{Rank}_{i,t-1}\right) + \delta X_{it} + c_i + s_t + u_{it}. \tag{5}$$

As in the previous equation, here B_j denote indicator variables that equal one if university i's lagged rank is in bin $j = \{1, 2, 3, 4, 5\}$. Each bin refers to an interval of 25 ranks. If the ranking effect is indeed stronger at better ranks, then I would observe that the estimates on the interaction terms, β_2^j, increase with higher rank bins.[15]

5.2 Frontpage Effect

In the second part of the econometric analysis, I study whether universities benefit from a "front page effect". In the print edition of the USN rankings, the best 50 universities are listed on the front page of the magazine, whereas subsequent universities are less favorably presented on the next page.[16] Therefore, potential applicants may

[15]Assuming a negative base effect, this means that the sum of the base effect and interaction term estimate decrease in absolute terms with higher rank bins.

[16]Cf. Bowman and Bastedo (2009) p. 421.

get the impression that universities on the second page of the magazine are inferior to the ones on the front page. This leads me to examine whether a university's placement among the top 50 systematically affects its admission outcomes in the following year.

This approach translates to a typical treatment analysis where the "treatment" in this case is defined as being ranked among the best 50 universities. Given that the treatment is perfectly determined by a university's ranking placement, a natural econometric approach to test the above hypothesis is with a regression discontinuity (RD) design (Lee and Lemieux 2010; Imbens and Lemieux 2008; Hahn, Todd, and Van der Klaauw 2001). The general idea is to compare the admission outcomes for universities placing just below the threshold of 50 with universities just above the threshold to replicate a local randomized experiment. If one can sustain the assumption that universities with close enough ranking placements are also similar in other characteristics, then treatment assignment can be considered as good as random and the difference in outcomes for universities just below and just above the 50th rank can be used to recover the effect of being ranking among the top 50.

In terms of the potential outcomes model, the causal effect of treatment formalizes to

$$Y_i(1) - Y_i(0), \tag{6}$$

where $Y_i(1)$ denotes the outcome of university i if it is treated and $Y_i(0)$ the outcome if it is not treated. To recover the true causal effect of treatment one would require that both outcomes are known. The major obstacle for drawing definitive conclusions, however, is that for each university, it is only possible to observe one of these outcomes at a time.[17] If a university is ranked in the top 50, I observe its realizations for the admission outcomes, but I do not observe the outcome realizations that would have occurred had it not been ranked in the top 50. Vice versa, the outcomes of a university placing outside the top 50 are known, but I do not observe its outcomes had it made it to the top 50.[18] If the RD approach is valid, universities just below the rank of 50 will be good approximations of the counterfactual outcome for universities just above the rank of 50 and thus allow the estimation of the treatment effect, that is

$$E[Y_i(1) - Y_i(0)|X_i = c] = \lim_{x \downarrow c} E[Y_i|X_i = x] - \lim_{x \uparrow c} E[Y_i|X_i = x], \tag{7}$$

where X is the running variable and c is the cutoff that perfectly determines receipt of

[17] Note that in the present context, one would strictly require an additional time index as it is possible that a university is both treated and not treated, albeit at different times.

[18] Cf. Imbens and Wooldridge (2009) pp. 4–7; Abadie and Cattaneo (2018) pp. 467–468.

treatment, $D = 1\{X \geq c\}$.[19]

In the simplest possible setting, this can be estimated by the following regression equation:

$$Y_i = \beta_0 + \beta_1 D_i + \beta_2 X_i + u_i. \tag{8}$$

Here, X is defined as the deviation of the running variable from the threshold so that β_1 identifies the effect of treatment at the threshold. Equation (8) assumes a linear relationship between the outcome Y and the running variable X, which in general need not be true. In such a scenario, the functional misspecification would introduce bias to the estimate.[20]

Applied to the university context, I estimate the effect of reaching the top 50 of the USN ranking using variations of the following equation:

$$Y_{it} = \beta_0 + \beta_1 D_{i,t-1} + f(X_{i,t-1}) + u_{it}, \tag{9}$$

where the dummy variable $D_{it} = 1\{\text{Rank}_{it} \leq 50\}$ indicates whether a university is treated or not and $f(\cdot)$ is a varying functional form of the ranking variable. Most frequently used functional forms range from simple linear functions (with or without restricting the same slope on either side of the cutoff) to higher oder polynomials. In Section 6, I present and discuss results for different functional forms and bandwidths alongside the main assumption upon which the validity of the RD approach rests.

6 Results

6.1 Baseline Effect

The results for the baseline ranking effect are presented in Table 6. Separate estimations for each dependent variable are shown in Panels A–G. Since there is no higher level of aggregation available where the errors are likely uncorrelated, I cluster standard errors at the university level. Each specification is a variation of equation (1) with a varying set of lagged control variables (the ranking factors) and fixed effects. I do not use reverse-coded ranks, so the estimates indicate expected changes from a worsening by one rank. All specifications also include an intercept. The number of applications, admissions, enrollments, and the tuition fee variables are log-transformed so that large

[19]Cf. Lee and Lemieux (2010) p. 288; Abadie and Cattaneo (2018) p. 492; Imbens and Wooldridge (2009) p. 59.

[20]Cf. Lee and Lemieux (2010) p. 316.

Table 6
Baseline Estimation Results

	No Fixed Effects		Year Effects		University & Year Effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. SAT Score [1268]							
Rank_{t-1}	-0.822^{***}	-0.874^{***}	-0.906^{***}	-0.886^{***}	-0.540^{*}	-0.478^{*}	-0.250
	(0.264)	(0.310)	(0.295)	(0.339)	(0.275)	(0.254)	(0.242)
Adjusted R^2	0.803	0.828	0.803	0.827	0.982	0.982	0.986
B. log(Applications) [23163]							
Rank_{t-1}	-0.483	-0.623^{*}	-0.896^{**}	-0.791^{**}	-0.029	-0.113	0.045
	(0.329)	(0.351)	(0.362)	(0.392)	(0.107)	(0.118)	(0.129)
Adjusted R^2	0.138	0.370	0.188	0.378	0.965	0.965	0.973
C. log(Admissions) [10522]							
Rank_{t-1}	-0.348	-0.638^{*}	-0.801^{**}	-0.971^{**}	0.136	0.213^{*}	0.224^{*}
	(0.346)	(0.367)	(0.381)	(0.402)	(0.122)	(0.126)	(0.129)
Adjusted R^2	0.343	0.543	0.380	0.564	0.980	0.980	0.985
D. log(Enrollments) [3290]							
Rank_{t-1}	-0.644^{*}	-0.713^{*}	-0.952^{**}	-0.944^{**}	0.057	0.096	0.097
	(0.375)	(0.368)	(0.412)	(0.402)	(0.088)	(0.097)	(0.093)
Adjusted R^2	0.221	0.514	0.239	0.526	0.990	0.990	0.992
E. Admission Rate [0.49]							
Rank_{t-1}	0.077	0.070	0.061	0.024	0.037	0.086	0.031
	(0.065)	(0.075)	(0.073)	(0.082)	(0.052)	(0.057)	(0.070)
Adjusted R^2	0.738	0.772	0.737	0.776	0.950	0.952	0.958
F. Yield Rate [0.35]							
Rank_{t-1}	-0.110^{*}	-0.041	-0.070	-0.006	-0.047^{*}	-0.077^{***}	-0.062^{**}
	(0.062)	(0.073)	(0.071)	(0.082)	(0.027)	(0.027)	(0.030)
Adjusted R^2	0.180	0.278	0.185	0.281	0.954	0.955	0.964
G. log(Tuition) [23550]							
Rank_{t-1}	0.540	0.330	0.459	0.301	0.041	0.091	0.032
	(0.332)	(0.305)	(0.373)	(0.341)	(0.056)	(0.061)	(0.048)
Adjusted R^2	0.419	0.674	0.416	0.673	0.994	0.994	0.998
Year Effects	No	No	Yes	Yes	Yes	Yes	Yes
University Effects	No	No	No	No	Yes	Yes	Yes
Control Set	Trade-off	Full	Trade-off	Full	None	Trade-off	Full
Observations	944	708	944	708	944	944	708

*Notes: Heteroskedasticity-robust standard errors clustered at the university level in parentheses. The estimated models are variations of equation (1) with varying controls and fixed effects. All models contain an additonal intercept. The rank variable is not reverse-coded, i.e., the estimates indicate effects of a worsening by one rank. All dependent variables except for the SAT score are multiplied by the factor 100 for visual convenience. Mean of dependent variables in square brackets. The trade-off control set contains lagged values of the graduation rate, retention rate, and instructional expenditure per student. The full set of controls additionally contains lagged values of the fulltime-faculty percentage, average faculty salary, and student-teacher ratio. Significance levels 1%, 5%, 10% denoted by ***, **, *, respectively.*

outliers do not cause as strong divergences from the normal distribution assumption.[21] Apart from the average SAT score, I also multiplied the dependent variables by the factor 100 for visual convenience, meaning that the estimates for the admission and yield rate correspond to percentage point changes, while the estimates for applications, admissions, enrollments, and tuition approximate percent changes. Each Panel also shows the (untransformed) mean of the respective dependent variable in square brackets to provide a better intuition for the magnitude of the estimated effects. The trade-off control set refers to the subset of the ranking factors discussed earlier and contains lagged values of the graduation rate, retention rate, and instructional expenditure per student. The full set of controls additionally include lagged values of the fulltime-faculty percentage, average faculty salary, and student-teacher ratio.

SAT Score—Across all specifications, the estimated rank effect has the expected sign with effect sizes ranging from -0.5 to -1. That is, a drop in the rankings by one rank is associated with a decrease in the average SAT score at a given university by 0.5 to 1 points. The size differences across specifications (1)–(4) are very small—once university fixed effects are introduced, however, the effect size decreases considerably. With it, the level of significance drops as well—so much that based on column (7), a true effect size of zero cannot be rejected at conventional levels. The effect sizes are, however, broadly in line with the results of related studies. In comparison, they are at the lower end of the results presented in Section 2 (-0.4 to -1.5), though it is worth noting that the SAT variable in my sample measures the average at a given university instead of the average SAT score of the incoming freshmen class in a given year. Provided that the average at a university is less prone to fluctuations than is the SAT score of incoming students in one specific year, one would expect the effect size on that variable to be lower. The relative magnitude of this effect is small: to increase the average SAT of its student body by only 10 points, an institution would need to improve its rank by roughly 20. To put this into perspective, only two of the 118 universities managed to do so over the timespan 2008-2015, and the average rank change between two consecutive years is 3.2. Besides that, I also find that specifications (3) and (4) do not provide more explained variation as seen by the adjusted R^2 compared to specifications (1) and (2), even though the SAT score at the universities evidently increased over the years.

Applications—Panel B shows the results of regressing the log of the number of applications on previous years' rank placement. Throughout almost all columns, the estimated effect is negative, suggesting a negative relationship between the number of

[21] For example, Figures 3-4 showed that some distributions of the dependent variables are highly skewed.

applications a university receives and its placement in the USN ranking. Here, only columns (3) and (4), which incorporate the overall time trend into the model, yield significant results. However, in the model specifications that I believe offer the best identification, i.e., specifications (6)–(7), the resulting estimates suggest no significant effect on the number of applications and even change sign when the full set of controls is included. Thus, these results contrast the findings of previous studies reporting negative effects on applications from a loss in the rankings (-0.4 to -1).

Admissions—The effects on admissions are inconsistent across the different specifications. While the effect of a one-rank loss appears to be negative in specifications that do not control for university effects, this effect becomes positive once university effects are included. The negative effects in columns (3) and (4) are also somewhat high, as they would indicate a decrease in admitted students by around 4-5% from a drop in ranks by five positions. As for columns (6) and (7), the effect is positive and much more moderate in comparison, although it is only significant at the 10% level.

Enrollments—I find a similar pattern of results for the number of enrollments. Without controlling for university effects, the estimates for a one-rank loss are negative and economically large, ranging from -0.65 to -0.95%. Once the unobserved heterogeneity is accounted for, the effect becomes positive and decreases to only one-tenth of the earlier effect size. At first glance, there is hence no indication that a university's USN rank affects how many students enroll at a university. Note also that enrollments are highly related to the number of students a university admits because the decision to enroll or not is conditional on being admitted by that university. The internal dependence of these two variables may be better captured by Panel F, where I regress the yield rate (= enrollments/admissions) on lagged rank.

Admission Rate—The point estimates for the admission rate are positive but insignificant across all specifications. In contrast to earlier results that unanimously report positive results by up to 0.5 percentage points per drop in the ranking, my results imply no significant effect on the admission rate. Moreover, with effect sizes between 0.03 and 0.08 percentage points, the effects are economically too small to be impactful unless a university caught up tremendously in the rankings.

Yield Rate—Panel F shows results on the yield rate, which is defined as the number of enrollments divided by the number of admitted students. The estimate for the rank effect is always negative, with effect sizes ranging between -0.047 and -0.077 percentage points per rank drop in columns (5)–(7). As in regressions for the other dependent variables, the effect size is again small in magnitude: for an increase in the yield rate by only one percentage point (the average in the sample is 0.35), a university

Table 7
Baseline Ranking Effect with Flexible Timing (1)

	SAT Score		log(Applications)		log(Admissions)		log(Enrollments)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rank_{t-1}	−0.426**	−0.391*	−0.053	−0.005	0.252**	0.199*	0.078	0.058
	(0.195)	(0.208)	(0.099)	(0.122)	(0.099)	(0.116)	(0.088)	(0.097)
Rank_{t-2}	0.071	0.159	0.013	−0.024	−0.003	−0.027	0.031	0.037
	(0.190)	(0.152)	(0.093)	(0.097)	(0.114)	(0.104)	(0.068)	(0.056)
Rank_{t-3}		0.088		0.186		0.191		0.090
		(0.241)		(0.156)		(0.129)		(0.090)
Baseline Estimate	−0.478*		−0.113		0.213*		0.096	
Baseline SE	(0.254)		(0.118)		(0.126)		(0.097)	
Adjusted R^2	0.984	0.986	0.971	0.973	0.983	0.985	0.991	0.992
Observations	826	708	826	708	826	708	826	708

*Notes: Heteroskedasticity-robust standard errors clustered at the university level in parentheses. The estimated models are variations of equation (2). All models contain an additonal intercept, university and time fixed effects, and the trade-off control set (lagged values for the graduation rate, retention rate, and instructional expenditure per student). The rank variable is not reverse-coded, i.e., the estimates indicate effects of a worsening by one rank. All dependent variables except for the SAT score are multiplied by the factor 100. To better compare how the estimates evolve across specifications, the baseline estimate and standard error refer to the model when only the first lag of rank is included. Significance levels 1%, 5%, 10% denoted by ***, **, *, respectively.*

would need to move up 13 ranks in the USN ranking. My estimates for the yield rate are also consistent with those from earlier studies reporting results around −0.1 percentage points per rank loss. As previously mentioned, the yield rate allows me to study the interplay between admissions and enrollments. Having access to separate regressions for admissions and enrollments, I can break down the effect on the yield rate. Given that yield is defined as enrollments divided by admissions, it seems as if the rank effect on yield is negative because a worse rank increases the denominator while the numerator remains unaffected. Hence, the ranking effect for the yield rate is primarily driven by an increase in the number of admissions.

Tuition—Finally, I do not find statistically significant results for whether universities adjust their tuition fees in response to changes in their USN ranking placement. I find this estimated effect to be consistent with the hypothesis.

Tables 7–8 shows the results of regressions that allow for a more flexible timing of the ranking effect based on equation (2). For every dependent variable, the tables show the model with $k = 2$ and $k = 3$. Every column controls for university and time fixed effects and includes the trade-off control set since the full set of controls would

Table 8
Baseline Ranking Effect with Flexible Timing (2)

	Admission Rate		Yield Rate		log(Tuition)	
	(1)	(2)	(3)	(4)	(5)	(6)
Rank_{t-1}	0.109*	0.055	−0.068***	−0.056*	0.077	0.046
	(0.059)	(0.069)	(0.023)	(0.030)	(0.053)	(0.052)
Rank_{t-2}	−0.052	−0.015	−0.017	−0.001	−0.033	−0.033
	(0.049)	(0.045)	(0.034)	(0.033)	(0.037)	(0.036)
Rank_{t-3}		−0.035		−0.039		−0.030
		(0.062)		(0.036)		(0.044)
Baseline Estimate	0.086		−0.077***		0.091	
Baseline SE	(0.057)		(0.027)		(0.061)	
Adjusted R^2	0.955	0.958	0.959	0.962	0.996	0.998
Observations	826	708	826	708	826	708

*Notes: Heteroskedasticity-robust standard errors clustered at the university level in parentheses. The estimated models are variations of equation (2). All models contain an additonal intercept, university and time fixed effects, and the trade-off control set (lagged values for the graduation rate, retention rate, and instructional expenditure per student). The rank variable is not reverse-coded, i.e., the estimates indicate effects of a worsening by one rank. All dependent variables except for the SAT score are multiplied by the factor 100. To better compare how the estimates evolve across specifications, the baseline estimate and standard error refer to the model when only the first lag of rank is included. Significance levels 1%, 5%, 10% denoted by ***, **, *, respectively.*

reduce the sample size even more than it is already due to the lagged rank variable. That is, each column is similar to specification (7) of the baseline effect estimations but extended by additional lagged ranking parameters. For easier comparability, I also included underneath each dependent variable the estimate from the specification with only the first rank lag, i.e., when $k = 1$.

For each dependent variable, it should not be the case that a significant effect for the first lag switches signs once the model is augmented by additional lags. Moreover, if information of past USN ranking editions still influence current realizations of the dependent variables, then one should observe that the effect size of the first lag diminishes when additional lags are added to the model, i.e., the total effect size is partly absorbed by the additional lags.

There is no change with respect to significant results for applications, enrollments, or tuition fees. As in earlier models, the placement in the rankings appears to be unrelated to these three outcomes. For the other dependent variables, one can observe minor changes in the absolute size of the effect and increased precision of the parameter estimates once the second lag is added to the model. Furthermore, the sign of estimates for which I found significant effects never changed following the inclusion of additional lags. Unanimously across all specifications, these additional lags are also never significantly different from zero, whether in models with two or three lags. Instead, significant and same-sign effects are exclusively seen for the first lag of rank. I take this as evidence that only the most recent rankings have an effect on current dependent variables, but not those from further back in time. Therefore, when scanning for information on university quality, once a new edition of the USN ranking is released, newer editions supersede earlier ones, making them obsolete information.

Table 9 summarizes the results for the analysis of heterogeneous effects. Panel A shows estimations of equation (3). The baseline ranking effect on the average SAT score was -0.478 ($p < 0.1$). Following the introduction of the interaction between the ranking effect and the indicator for private institutions, the absolute effect size doubles for private universities but is statistically zero for public universities. This would suggest a moderate increase in the quality of students at a given university: for every improved rank, a university's average SAT score would increase by roughly 1 SAT point, on average. Somewhat surprisingly, Panel A only shows significant effects for private universities. There is a (weakly) significant effect with respect to the admission rate of private universities ($p < 0.1$), but it is hard to conclude whether this is driven by increased admissions or decreased applications without significant effects for either. Private universities also appear to react to a one-rank loss with increased tuition fees by around 0.2%. I find no such effect for public universities. Moreover, the baseline ranking effect on the yield rate (-0.077, SE of 0.027) vanishes when allowing for heterogeneous effects. The baseline effect for the yield rate must therefore be based on another underlying variable.

Such a variable could be the size of a university since admission processes and governance regimes are likely to be different between institutions that admit several thousand students and those that only admit very narrow groups of students. Figure 8 illustrates how size, ranking placements, and control of the sample universities are related. Especially the left plot shows that a cut at around 2500 undergraduate students separates the universities very well in terms of public and private. Similarly, universities with an average rank below 25 are predominantly private ones. The separate study of effect heterogeneity based on control, size, and relative rank placement thus allow me to test whether the results for, e.g. private universities, are in fact simply due to private universities being small or placing better.

Panel B summarizes estimates according to equation (4). Here, medium and large denote indicator variables that equal one if a university has between 2000 and 5000,

Table 9
Effect Heterogeneity

	SAT	App.	Adm.	Enr.	Adm. Rate	Yield	Tuition
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Heterogeneity by Control							
Rank_{t-1}	0.0004	−0.038	0.167	0.151	0.008	−0.058	−0.034
	(0.285)	(0.136)	(0.171)	(0.148)	(0.075)	(0.041)	(0.093)
$\text{Rank}_{t-1} \times$ Private	−0.930**	−0.145	0.090	−0.107	0.151*	−0.038	0.242**
	(0.443)	(0.212)	(0.226)	(0.170)	(0.090)	(0.053)	(0.110)
Adjusted R^2	0.983	0.965	0.980	0.990	0.952	0.955	0.994
Panel B. Heterogeneity by Size							
Rank_{t-1}	−0.465*	−0.123	0.176	0.016	0.059	−0.081***	0.097
	(0.237)	(0.118)	(0.130)	(0.080)	(0.060)	(0.030)	(0.064)
$\text{Rank}_{t-1} \times$ Medium	−0.016	0.006	0.042	0.098***	0.038	0.005	−0.011
	(0.061)	(0.034)	(0.064)	(0.021)	(0.029)	(0.013)	(0.020)
$\text{Rank}_{t-1} \times$ Large	0.005	−0.079	−0.063	−0.021	0.040	0.009	−0.033
	(0.100)	(0.060)	(0.088)	(0.069)	(0.035)	(0.021)	(0.043)
Adjusted R^2	0.982	0.965	0.981	0.991	0.952	0.955	0.994
Panel C. Heterogeneity by Rank Placement							
Rank_{t-1}	−1.529***	−0.586	−0.044	−0.172	0.149	−0.107	−0.047
	(0.459)	(0.388)	(0.388)	(0.140)	(0.115)	(0.146)	(0.181)
$\text{Rank}_{t-1} \times [25, 50]$	0.812***	0.250	0.129	0.163***	−0.019	0.020	0.018
	(0.313)	(0.312)	(0.281)	(0.056)	(0.082)	(0.113)	(0.163)
$\text{Rank}_{t-1} \times [50, 75]$	0.800**	0.269	0.206	0.255***	−0.0004	0.026	0.095
	(0.354)	(0.324)	(0.315)	(0.082)	(0.094)	(0.122)	(0.173)
$\text{Rank}_{t-1} \times [75, 100]$	0.865**	0.352	0.237	0.260***	−0.012	0.027	0.077
	(0.367)	(0.332)	(0.325)	(0.086)	(0.095)	(0.126)	(0.172)
$\text{Rank}_{t-1} \times [100, 125]$	0.929**	0.373	0.207	0.242***	−0.037	0.030	0.096
	(0.367)	(0.337)	(0.333)	(0.091)	(0.096)	(0.129)	(0.173)
$\text{Rank}_{t-1} \times [125, 150]$	0.948**	0.402	0.270	0.278***	−0.030	0.024	0.118
	(0.374)	(0.342)	(0.341)	(0.103)	(0.097)	(0.130)	(0.173)
Adjusted R^2	0.982	0.965	0.981	0.990	0.952	0.955	0.994
Observations	944	944	944	944	944	944	944

*Notes: Heteroskedasticity-robust standard errors clustered at the university level in parentheses. Panel A shows estimates for equation (3), Panel B those for equation (4), and Panel C shows estimates for equation (5). All models contain an additonal intercept, university and time fixed effects, and the trade-off control set. Significance levels 1%, 5%, 10% denoted by ***, **, *, respectively.*

or more than 5000 undergraduate students, respectively. The reference group is small universities. The effect of a one-rank loss does not appear to be different based on the size of a university. Only the non-interacted estimate, referring to small universities, is significant at the 10% level and very similar to the baseline effect (−0.478, SE 0.254), likely absorbing some of the effect size of private universities due to the aforementioned large overlap. I find significant effects only for the number of enrollments and the yield

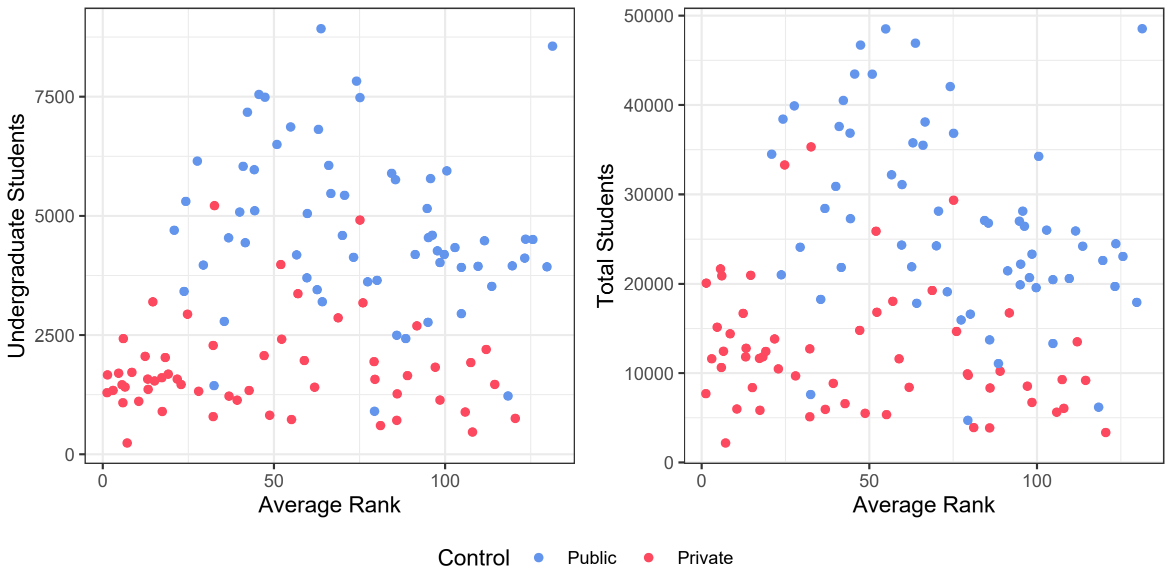

Figure 8: Relationship between University Size, Rank, and Control

rate. Oddly, a drop by one rank in the USN ranking leads to an increase in enrollments at medium-sized universities by a little over 0.1%. I find this estimate difficult to interpret, as one would not expect enrollments to increase when universities drop in the standings—one possible explanation for this effect is given later when looking at Panel C. Finally, the point estimate for the yield rate of small universities is almost identical to the baseline effect estimate (-0.077, SE 0.027). This leads me to conclude that primarily small universities show significant yield rate responses but not larger universities.

As a last heterogeneity check, I examine whether movements within top ranks induce stronger effects than movements within worse ranks. Panel C shows estimates based on equation (5). I find statistically significant ranking effects for the SAT score and for the number of enrollments. For the SAT score, the pattern of the effect sizes for interactions with different rank bins confirms the hypothesis that movements within top ranks have stronger effects on the SAT score than movements within poorer ranks. While a one-rank drop leads to an SAT score decrease by 1.5 points for movements within the top 25, the effect size diminishes gradually with a worse relative placement in the ranking. The suggested effect is only about half as strong (-0.7) for movements between ranks of 25 and 50 and about one-third as strong (-0.5) for movements between ranks of 125-150. Therefore, losing a spot in the top placements has much more severe implications for the average SAT score at a university than losing a spot at relatively worse placements. Lastly, I find a similar pattern for the number of enrollments. The effect of a one-rank loss is negative but not statistically significant in the top 25, becomes positive and significant at movements in ranks larger than 50, then increases gradually the further down one goes in the ranking. Similar to Panel B, the sign of this effect is at odds with my earlier hypothesis. Given that enrollment decisions are conditional on being admitted by a university, it could be that rank changes affect *which* students a university admits. For example, institutions could specifically admit applicants who they think are most likely to enroll. In this case, rank changes would also affect the composition of admitted students and one would observe such positive estimates as in column (4). Unfortunately, testing this requires richer data on the applicant/student level, which my sample does not contain.

As a complementary sensitivity check, I briefly test whether the estimates are significantly different under the full control set and the trade-off control set, which consists of fewer ranking factors. Since the complete control set contains the (lagged) student-faculty ratio, for which I do not have data for the years 2006 and 2007, using this set effectively drops the years 2008 and 2009 from my data and hence leads to undesired loss of information. The resulting estimate differences when using the two control sets can thus also be affected by these two missing years of observations. To remedy this, I impute the missing values for the student-faculty ratio for 2006 and 2007 by a university's student-faculty ratio from 2008. I justify this approach by the fact that the student-faculty is a highly stable metric for the majority of the universities in the sample. In fact, many universities remained at plus-minus two of the same student-faculty ratio over the entire sample period.

Table A1 shows the resulting estimates when the full set of controls with imputed student-faculty ratios is used. The only dependent variable for which I find different significance levels is the tuition fee. Here, the estimate changes from $\beta = 0.091$ (SE 0.061) to $\beta = 0.124$ (SE 0.062). Overall, the inclusion of the additional controls causes the effect size to drop only slightly in absolute magnitude. I conclude that the differences between specifications (6) and (7) in Table 6 are mostly due to the two missing years of observations rather than the added control variables.

6.2 Frontpage Effect

In this final section, I examine the effect of being listed on the front page of the USN rankings' print edition. Universities that placed among the top 50 were listed on the front page, whereas universities that placed below this threshold were listed on the second page. Because this effect of being on the front page (treatment) is rule-based, a straightforward strategy to estimate the effect of treatment is via a regression discontinuity approach.

Figures 9–10 illustrate possible discontinuous jumps for the admission outcomes at the rank of 50. The grey points are the original data points, whereas the red points indicate binned-together observations. I used a bandwidth of $h = 20$ ranks below and above the rank of 50. The plots suggest no graphical evidence for discontinuities in the SAT Score, admission rate, yield rate, or tuition fees. Note that I used separate graphs for private and public tuition fees because the universities differ significantly in this aspect. Ignoring this would probably yield spurious results for the estimation of a treatment effect if there is only a slight imbalance between private and public universities around the threshold. For better comparability, Figure B3 shows both public and private universities in the same graph. Concerning the number of applications, there is weak graphical evidence for a discontinuous jump in the regression function at a rank of 50. Clearer discontinuities are visible for the number of admission and enrollments at a university. Here, there appears to be a distinctive increase in both outcomes for universities that just managed to be ranked among the top 50 versus universities that barely missed this threshold.

Table 10 shows the results for the estimation of the effect of being ranked in the top 50. As shown in the graphs, the number of applications, admissions, and enrollments as well as the tuiton fee are not log-transformed but divided by 1000 for notational convenience. All regressions further control for university and year fixed effects as well as the sparse control set. When employing an RD approach, there does not seem to be a consensus in the literature on whether fixed effects should be included in an RD setting given that the validity of the approach does not depend on the inclusion of fixed effects. One benefit may be, however, a lower sampling variance.[22] To be consistent with the estimations for the baseline effect, I decided to include university and time effects. Moreover, separate estimates are reported for effects on tuition fees for public and private universities as explained earlier.

The estimates are based on local linear regressions with a varying bandwidth (denote by h) below and above the rank of 50. Except for column (1), which allows for a more flexible quadratic functional form, all specifications assume a linear relationship between the outcomes and the ranking variable and allow for different slopes around either side

[22] Cf. Lee and Lemieux (2010) pp. 337–338.

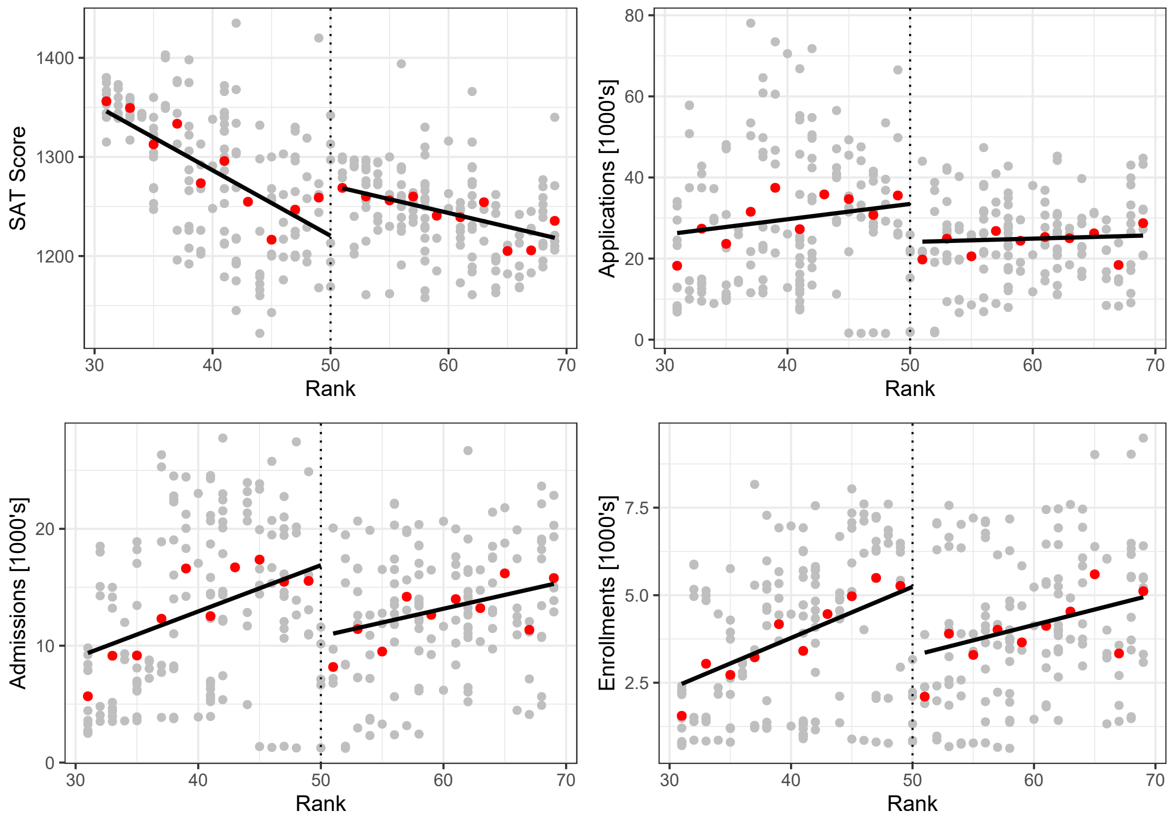

Figure 9: Relationship between Outcomes and Ranking Placement (1)

of the threshold. That is, formally, I estimate the following equation:

$$Y_{it} = \beta_0 + \beta_1 D_{i,t-1} + \beta_2 R_{i,t-1} + \beta_3 (R_{i,t-1} \times D_{i,t-1}) + \delta X_{it} + c_i + s_t + u_{it}, \tag{10}$$

where $D_{it} = 1\{\text{Rank}_{it} \leq 50\}$ and $R_{it} = \text{Rank}_{it} - 50$. Therefore, the results in the table correspond to estimates of β_1.

In contrast to the graphical evidence, I find no statistically significant effect on admission outcomes for placing in the top 50 of the USN ranking. The signs of the estimates also provide no clear indication of whether being listed on the front page has a positive or negative impact on the admission outcomes. For example, one would expect a positive effect on the SAT score, but the estimates are negative throughout all specifications. Moreover, for the majority of the outcomes, the sign and size of the effect is considerably different between the specifications—even across columns (3)–(5) where the bandwidth is only reduced in increments of 5 ranks. Therefore, I report no apparent front page effect, with the caveat that the estimates seem to be rather inconclusive.

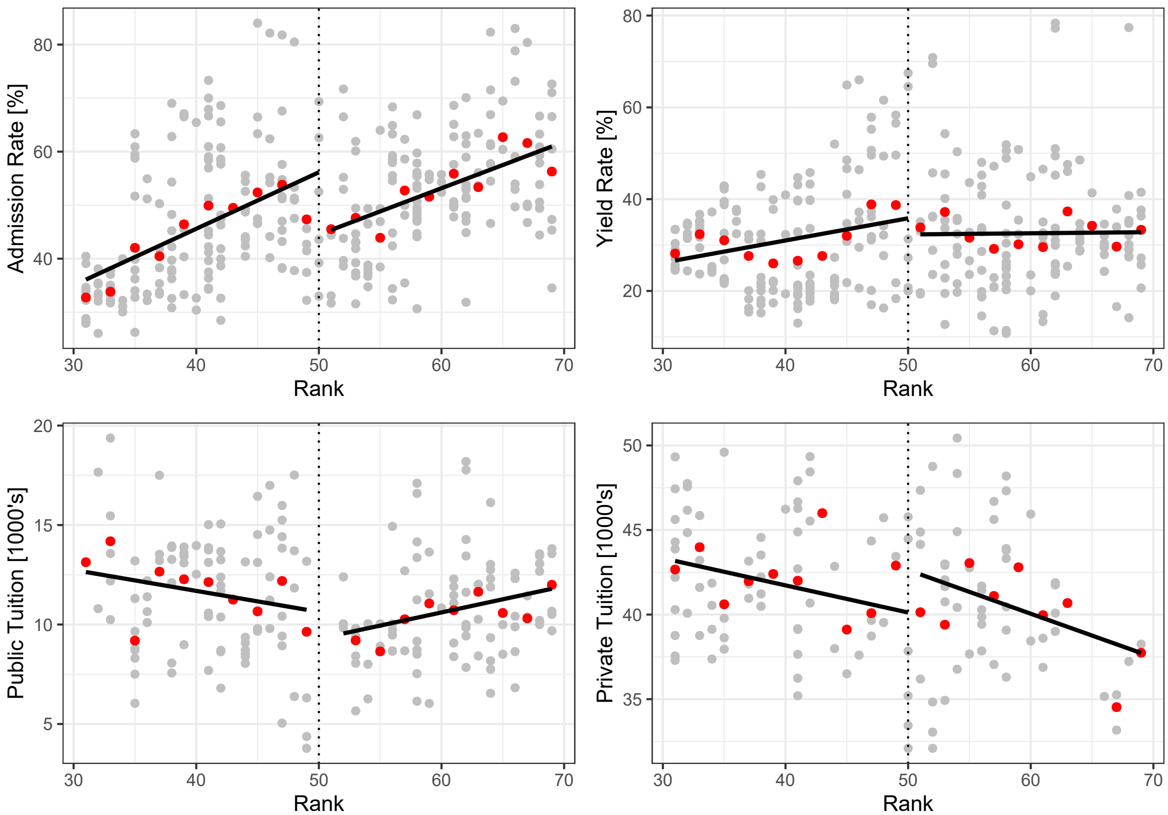

Figure 10: Relationship between Outcomes and Ranking Placement (2)

The validity of the RD approach rests on the assumption that the running variable cannot be manipulated. If this was the case, one would observe that entities clump right around the threshold that determines the treatment. This can plausibly be ruled out since a university's ranking is calculated based on an objective formula, and mass points around either side are by nature of a ranking already impossible. For example, if a university moved into the top 50 in one year, it would take the place of another and "crowd out" the limited ranks instead of generating mass points. The only exception for this would be when universities are tied for one rank, which occasionally is the case in the USN ranking. However, even then university administrators would need to be able to tell exactly on which rank the university would end up in the ranking and adjust the underlying ranking criteria such that it would just move into the top 50. Therefore, manipulation of the ranking variable is only possible under very restrictive assumptions. Nonetheless, Figure B4 shows graphical evidence against manipulation around the threshold. If no manipulation is possible, then one should observe that the distribution is smooth around its support. As expected, there is no indication

Table 10

Regression Discontinuity Results

	$h = 50$		$h = 20$	$h = 15$	$h = 10$
	(1)	(2)	(3)	(4)	(5)
A. SAT Score					
Top 50	−1.746	−1.068	−4.682	−1.014	−0.459
	(5.036)	(4.535)	(4.626)	(4.934)	(5.481)
Adjusted R^2	0.983	0.982	0.956	0.953	0.954
B. Applications					
Top 50	1.136	0.501	0.099	−0.159	0.261
	(1.282)	(1.152)	(1.331)	(1.358)	(1.492)
Adjusted R^2	0.927	0.927	0.933	0.943	0.945
C. Admissions					
Top 50	−0.119	−0.487	−0.429	−0.300	0.205
	(0.476)	(0.427)	(0.426)	(0.442)	(0.505)
Adjusted R^2	0.964	0.964	0.966	0.968	0.971
D. Enrollments					
Top 50	0.021	−0.094	−0.031	−0.010	0.044
	(0.092)	(0.082)	(0.103)	(0.099)	(0.108)
Adjusted R^2	0.984	0.984	0.982	0.986	0.988
E. Admissions Rate					
Top 50	0.303	−0.695	0.023	0.181	0.390
	(1.624)	(1.460)	(1.714)	(1.889)	(2.166)
Adjusted R^2	0.956	0.956	0.854	0.821	0.823
F. Yield Rate					
Top 50	0.464	−0.165	0.426	0.783	0.441
	(1.082)	(0.971)	(0.778)	(0.729)	(0.829)
Adjusted R^2	0.960	0.960	0.968	0.980	0.982
Observations	763	763	300	226	155
G. Public Tuition					
Top 50	0.190	0.063	0.015	0.050	0.153
	(0.403)	(0.362)	(0.422)	(0.399)	(0.576)
Observations	366	366	180	139	87
Adjusted R^2	0.943	0.943	0.928	0.945	0.943
H. Private Tuition					
Top 50	−0.483	−0.267	−0.357	−0.009	0.123
	(0.447)	(0.389)	(0.324)	(0.312)	(0.323)
Observations	397	397	120	87	68
Adjusted R^2	0.984	0.984	0.992	0.994	0.988

*Notes: Cluster-robust standard errors in parentheses. Each Panel shows the estimated effect of being in the top 50. The bandwidth around the threshold is denoted by h. Columns (2)–(5) model the running variable in a linear way and allow for differnt slopes at either side of the threshold. Column (1) assumes a more flexible fit with a polynomial of order 2. All columns contain an additonal intercept, university and time fixed effects, and the trade-off control set. Significance levels 1%, 5%, 10% denoted by ***, **, *, respectively.*

of manipulation at the cutoff, but a few gaps at different ranking placement. These can, however, be explained by the fact that ties are possible in the USN ranking. For example, when there was a tie with, say 3, universities tied for rank 10, then the numerical ranks of 11 and 12 would not be given to the next best universities. It would receive a rank of 13 instead. Therefore, even the gaps at different ranks overestimate the chances of manipulation.

7 Conclusion

In this paper, I empirically study whether and to what extent the placement in the USN Best National Universities Ranking affects several admission outcomes of the ranked universities. My empirical analysis contains two parts. The first part evaluates the expected effect of moving one rank up or down in the ranking and makes suggestions about the underlying mechanisms that trigger these effects. The second part examines whether universities benefit from being listed on the first page of the rankings' print edition compared to being listed on the next, less conspicuous page instead.

Using ranking data from the years 2008–2015 of 118 high-profile U.S. universities in conjunction with administrative data from the Integrated Postsecondary Education Data System (IPEDS), I find that a worse rank leads to a lower percentage of admitted students that chose to enroll at a given university. Additionally, some results show a pronounced heterogeneity. My results suggest that private universities increase their tuition fee and that the quality of their students (as measured by the SAT score of its students) declines following a drop in the ranking. The economic consequences of this effect are small, however: for noticeable improvements in student quality, a university would need to manage a never-seen-before catch-up process in the ranking. Moreover, I find that the effect of a one-rank loss is much stronger for movements within the top ranks. While universities that drop a rank within the top 25 experience a decrease in the average SAT by about 1.5 points per rank, universities that drop a rank within the top 100-150 experienced only about a third of this effect's size. This suggests that competition at the very top is fierce and that prestigious institutions have more skin in the game than less prestigious ones. Heterogenous effects with respect to the relative position of the ranks are also found for the number of enrollments. While negligibly small at good ranks, institutions at relatively worse placements experience more enrolled students when losing a rank. This finding is largely at odds with theoretical expectations as one would expect that the perceived quality of a university declines when it loses a rank. Given that enrollments are conditional on the students that were admitted, it may be that universities adjust the composition of students that it admits, which then also affects the number of enrollments. However, this requires richer data on the individual applicant level, which my sample does not contain. This is a limitation of my study.

The findings of the second empirical part provide no evidence for a frontpage effect. None of the studied admission outcomes appear to be significantly affected by whether a university is listed on the first page of the printed USN ranking edition or on a subsequent, less conspicuous page. This result contrasts with other empirical works which report such effects.

My results have some implications for U.S. higher education. First, despite its great media reach and popularity, the USN Best National Universities Ranking has only little effect on the outcome of the universities' admission processes. It seems as if the ranking's impact on application and admission decisions is overstated, given that its effect is small at best. Second, the criticism directed to the ranking and its methodology has been discussed extensively by many authors. On grounds that university administrators would go as far as to adjust the admission process in order to augment the criteria for the ranking formula, my results provide support as to why the ranking is so strongly questioned and critically viewed in the public eye.

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Appendices

A Tables

Table A1

Sensitivity Check

	SAT	App.	Adm.	Enr.	Adm. Rate	Yield	Tuition
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rank_{t-1}	-0.408^{*}	-0.071	0.172	0.099	0.058	-0.059^{**}	0.124^{**}
	(0.231)	(0.112)	(0.127)	(0.098)	(0.059)	(0.027)	(0.062)
Adjusted R^2	0.982	0.965	0.981	0.990	0.952	0.957	0.994
Observations	944	944	944	944	944	944	944

*Notes: Heteroskedasticity-robust standard errors clustered at the university level in parentheses. Estimates compare to those of specifications (6) and (7) of Table 6 but include the whole set of controls with imputed values for the student-faculty ratio. All models contain an additonal intercept as well as university and time fixed effects. Significance levels 1%, 5%, 10% denoted by ***, **, *, respectively.*

B Figures

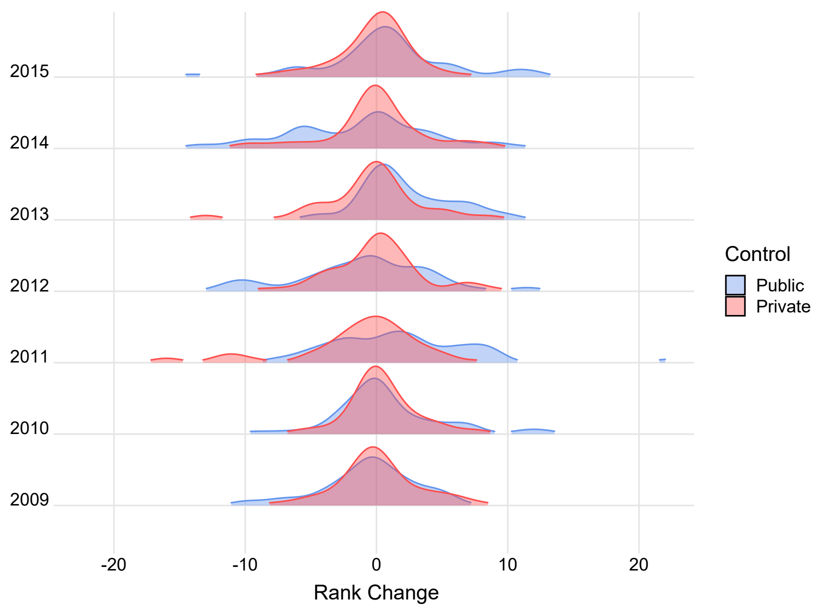

Figure B1: Trend of Rank Change Distributions

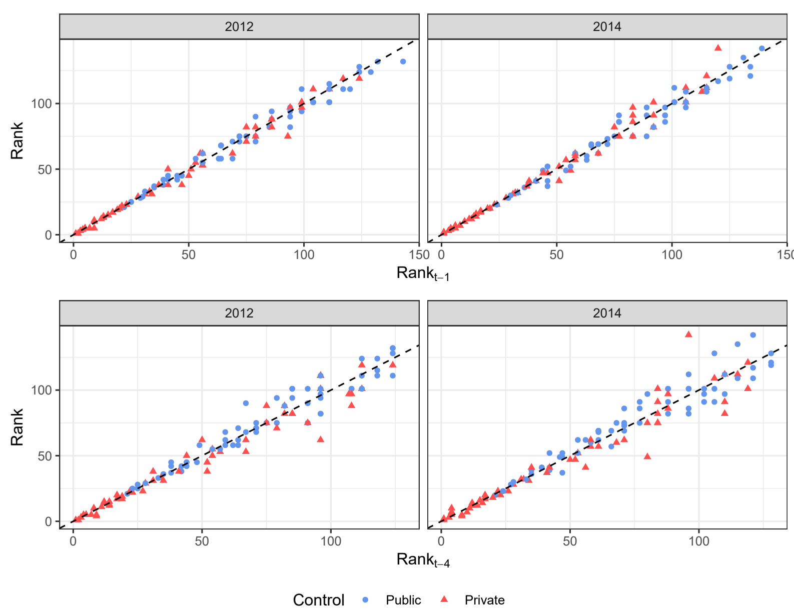

Figure B2: Rank Correlation with First and Fourth Lag

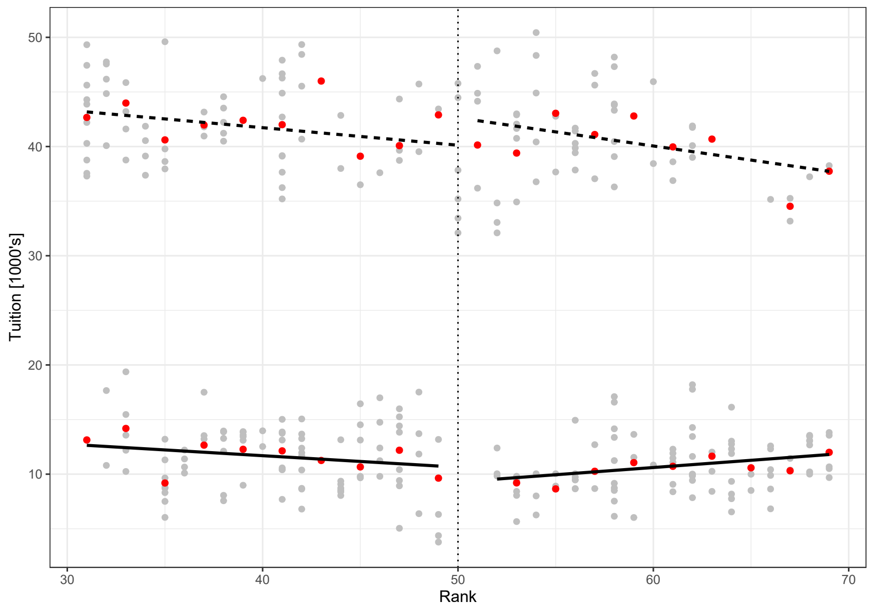

Figure B3: Relationship between Tuition and Ranking Placement

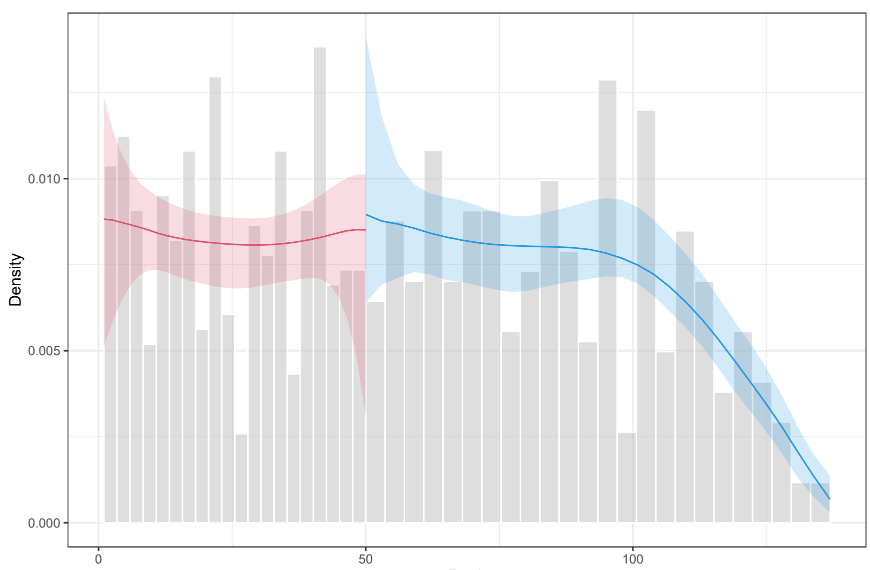

Figure B4: Density Test

Declaration of Authorship

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