

Salience in Quality Disclosure: Evidence from the *U.S. News* College Rankings

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Abstract

This paper investigates the impact of college rankings, and the visibility of those rankings, on students' application decisions. Using natural experiments from *U.S. News and World Report* College Rankings, we present two main findings. First, we identify a causal impact of rankings on application decisions. When explicit rankings of colleges are published in *U.S. News*, a one-rank improvement leads to a 1-percentage-point increase in the number of applications to that college. Second, we show that the response to the information represented in rankings depends on the way in which that information is presented. Rankings have no effect on application decisions when colleges are listed alphabetically, even when readers are provided data on college quality and the methodology used to calculate rankings. This finding provides evidence that the salience of information is a central determinant of a firm's demand function, even for purchases as large as college attendance.

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1. Introduction

A central assumption in industrial organization is that people optimize consumption decisions with respect to the price and quality of a good. In practice, product quality often has countless dimensions, which can make the decision process difficult. A growing literature has shown, furthermore, that consumers do not use all available information (Dellavigna and Pollet, 2007, 2010); instead, the decision depends on the simplicity of calculating the information of interest, or the “salience” of that information.³ In particular, the salience of tax systems has been shown to affect demand elasticity with respect to tax rates (Chetty et al., 2009; Finkelstein, 2009) even though, from a neoclassical perspective, responses to salient tax rates and opaque tax rates should be equivalent. A related literature shows that information aggregation is valuable to consumers with limited attention (Pope, 2009; Luca, 2010). Despite the growing evidence that consumers do not use all available information, intuition may continue to suggest that consumers are more likely to be attentive when making larger purchases. For example, the theory proposed by Chetty et al. (2009) predicts that consumers are more likely to pay attention to opaque details (in their case, taxes) when “making large, one time choices (e.g., buying a house) than when making small, repeated purchases (e.g., food, clothing).”

We investigate whether the salience of product-quality information affects demand in a setting where consumers choose among many options to make a large one-time investment: college. Empirically, we exploit a natural experiment to determine whether the *U.S. News and World Report* College Rankings (hereafter referred to as USNWR) has a larger impact on student application decisions when rankings are more salient. In our context, salience is defined in terms of the simplicity of determining a given college’s ranking. Thus if USNWR explicitly published a ranking, it would be more salient than if USNWR published only the underlying quality and a methodology for computing the ranking. Publishing rankings makes them less costly for applicants to compute, and also makes the information more readily visible.

We perform our analysis in two steps. First, we identify the causal impact of USNWR rank on equilibrium applications. Hence we can treat rank as a dimension of quality that college applicants value. Second, we show that application elasticity with respect to rankings is affected by the salience of the ranking system. The existing literature on salience is primarily focused on taxation (and hence elasticity with respect to price changes), but we show that salience also affects responsiveness to quality information. We also show that salience is important for large one-time purchases.

USNWR is an important setting in which to study the salience of quality information. It has become the dominant source of college rankings for schools, students, and news outlets. In 2007, within three days of publishing the rankings, the USNWR website received 10 million views, as compared to the typical month’s 500,000 views.⁴ Magazine sales often double relative to other months. Given the importance of college choice and the substantial influence of

³ This is the definition used by Chetty, Looney, and Kraft (2009).

⁴ Samuel Freedman, “Putting a Curious Eye on a High School Ranking System,” *New York Times*, December 5, 2007.

USNWR, the impact of its rankings are of direct interest. More generally, the impact on a firm's demand function of information and of how that information is presented is a central question in industrial organization.

An existing literature on college rankings has investigated USNWR. Monks and Ehrenberg (1999) show a correlation between rankings and application decisions, but do not distinguish changes in rank from changes in school quality. Meredith (2004) uses a similar strategy but focuses on differential effects by quality tiers for a broader set of schools. Griffith and Rask (2007) use student-level data to show the effect of rankings on matriculation decisions; Bowman and Bastedo (2009) show the nonlinear effect of several outcome variables on being ranked in the top 50. Our paper provides further evidence of the causal impact of rankings on application decisions, and it is the first publication to examine the salience of rankings.

To identify the causal impact of rankings, we exploit several methodological changes made by USNWR. In the 1990s, USNWR changed its ranking methodology six times. During that period, a school's ranking could move up or down from one year to the next without any accompanying change in objective quality measures. A striking example is the California Institute of Technology, whose rank rose from ninth in 1998 to first in 1999 entirely due to a change in methodology.⁵ Controlling for the underlying quality of schools, we find that an exogenous one-rank improvement leads to a 0.96-2.07 percent increase in applicants. We take this as evidence that USNWR has a causal impact on students' preferences. Our estimates reinforce the significant evidence that rankings themselves have a causal impact on application decisions. Pope (2009) finds consistent results when using hospital rankings.

If we treat a school's rank as a quality dimension to which students assign value, we can then test the impact of the salience of quality disclosure. To do so, we exploit a natural experiment. Prior to 1995, schools ranked 26-50 were pooled as "second-tier," while the "first-tier" schools were assigned explicit ordinal ranks from 1 to 25. After 1995, "second-tier" schools also assigned an explicit ordinal rank from 26-50. In other words, schools 26-50 were listed alphabetically before 1995 and listed according to rank after that year. Hence, rankings are more salient when they are explicitly listed numerically than when the schools are listed alphabetically. If salience matters, the impact of rankings on applications should increase when ranks are explicit.

To test for salience, we begin by constructing rankings using the underlying data and weights available to readers of USNWR. True rank cannot be perfectly predicted because USNWR does not publish faculty salaries, which affect rank. Furthermore, weights are only published for certain broad categories, which can consist of several pieces of information.⁶ For example, "selectivity rank" consists of SAT /ACT scores of incoming students, the proportion of enrolled freshmen who were in the top 10 percent of their high-school class, and the admissions acceptance rate. USNWR used a consistent method to construct rankings for all schools in all

⁵ Had there been no methodology changes in 1999, CIT would have dropped rather than risen in the rankings.

⁶ In a given year, three or four of the six broad categories consist of only one underlying piece of information, which is published.

years; the only difference between the alphabetically-ordered regime and the rank-ordered regime is that the latter makes the rankings visible and thus more salient. We find that when the rankings are opaque (the alphabetical regime), they have no significant impact on application decisions. Salient rankings, by contrast, have a large impact. Hence the impact of rankings depends not just on their informational content but also on their salience. We show that this result is robust to many alternative methods of constructing rankings and to other robustness checks.

Overall, our results suggest some facts about quality disclosure that run counter to standard intuition. Standard models to the contrary, elasticity with respect to quality changes does not depend solely on preferences and information availability; it also depends on how that information is presented. While salient rankings have a very large impact on demand, the same information presented in an opaque fashion has no impact on demand. From a quality-disclosure perspective, providing more information to consumers can actually reduce responsiveness and thus undermine the purpose of disclosure.

The paper proceeds as follows. Section 2 describes the data. Section 3 presents the estimation strategy. Section 4 presents the main results, and Section 5 concludes.

2. Data and Background

USNWR has published a ranking of U.S. colleges and universities every year since 1983, with the exception of 1984. Initially rankings were provided only for the top 13 universities, and they were based solely on a subjective survey of academics. Today hundreds of schools are ranked or assigned to tiers on the basis of a detailed survey of both objective and subjective quality measures. Using this data, USNWR publishes three hierarchical levels of information: (1) quality of several vertical dimensions (e.g., faculty resources, peer assessment, SAT scores, etc.), (2) a cardinal quality score (normalized so that the top school has a score of 100) computed as a weighted average of the category scores, and (3) an ordinal ranking based on the cardinal quality score.

In 1989 USNWR ranked the top 25 universities; the next 25 schools were listed alphabetically. The underlying data was published for all schools, but the cardinal score and rank were only published for the top 25 schools. In 1995 USNWR expanded its rankings to include the top 50 schools. Thus schools 26-50, formerly listed alphabetically, began to be explicitly ranked; in both cases, the underlying information was published alongside the listings.

In addition to expanding the rankings, USNWR also changed its ranking methodology (the weight assigned to each category) several times during the 1990s.⁷ Thus a school's rank could change from one year to the next even if no change in quality had occurred.

Our dataset consists, first, of rankings and underlying information for the top 25 schools, according to the 1990 rankings, over the period 1990-2000.⁸ Furthermore, for several tests we

⁷ By the late 1990s, USNWR also published the rankings online. We use the rankings in the magazine, which does not change the set of colleges we consider.

⁸ We could have considered a larger set of schools, but this time period offers clear identification strategies for only the top-ranked schools.

use the entire set of top 50 schools, as determined in 1995; these schools are listed in Appendix A, where the top 25 schools (in 1990) are denoted with an asterisk. The result is a nearly balanced panel.⁹

USNWR is published in the fall and employs data collected the previous year. Thus the 1999 “Best Colleges” issue appeared in the fall of 1998 and used surveys and data from applicants and enrolled students for the 1997-1998 academic year.

2.1. College Applications

We focus here on the top 50 schools in the USNWR during the period 1990-2000. These schools are highly competitive: on average, 72 percent of their applicants were in the top 10 percent of their class, and the average SAT score was 1267. The schools are also highly selective, accepting fewer than half of all applicants. Though this group of schools does not represent the typical college-going population, it does make an interesting case study because such students presumably put a lot of effort into choosing a college. We do not know how many applications each student in our sample submitted. However, Smith (2011) shows that high-school seniors apply to an average of approximately three colleges (conditional on applying to at least one).

Some of our specifications use tier-1 schools as a control group for tier 2. This might be problematic if applications to tier-1 schools trended differently from tier-2 schools. Figure 1 shows, however, that the two groups exhibit similar trends in application patterns during the period in question.

This is also a time in which applications became available over the internet and the Common Application went from 124 colleges to 209.¹⁰ Along with increased four-year college enrollment of approximately 9 percent (NCES 2002), potentially contribute to the increase in total number of applications seen in Figure 1. Simultaneously, the internet reduced the circulation of USNWR but at the same time, allowed for online viewership.

2.2. USNWR Quality Categories

The structure of the quality measures in USNWR is hierarchical. Detailed information is aggregated into the following broad published variables: reputation rank, selectivity rank, faculty-resource rank, retention and graduation rank, financial-resources rank, and alumni-giving rank.¹¹ The broad variables are treated as ordinal ranks; a ranking of 1 is the best possible

⁹ During the early segment of the sample, data was only published for the top 25 schools. If a school was in the top 25 in 1990 but fell below the top 25 in subsequent years, the data is missing. This is the case for UNC (1992-1994), UCLA (1994), and the University of Rochester (1991-1994). After 1994, partial data only was published for schools ranked outside the top 25. This was the case for CMU (1996), UNC (1995), UCLA (1995-1996), UC-Berkeley (1995-1996), and the University of Rochester (1995-1996). An unbalanced panel of the top 25 schools produced fewer observations with complete data. We also considered using the 2000 rankings to select a balanced set of schools, but it only produced changes in the rankings of a few schools.

¹⁰ Information from www.commonapp.org.

¹¹ In certain years, some of these variables were not assigned an ordinal rank but instead a continuous quality measure. We converted those continuous scores into ordinal ranks.

outcome relative to all other schools surveyed, both in and out of the top 50. Reputation rank is determined by asking university presidents, provosts, and deans of admissions to rank other schools' reputations. Selectivity rank is a linear combination of several more detailed variables, including SAT and ACT scores, the proportion of enrolled freshmen who were in the top 10 percent of their high-school class, and the admissions acceptance rate. Faculty-resource rank is based on the percent of classes with fewer than 20 students, the percent of classes with more than 50 students, the percent of faculty with Ph.D.s, full-time faculty as a percentage of all faculty, and the student-faculty ratio. Retention and graduation rank are based respectively on the percent of freshmen who return the next year and the percent of students who graduate. Financial-resources rank is based on educational expenditures per student and non-educational expenditures per student. Alumni-giving rank measures the percentage of alumni who donate.¹²

These broad categories are transparent and relatively constant over the period in question,¹³ but the methodology underlying these categories has been neither constant nor completely transparent. Therefore we primarily use the broad measures of quality but sometimes use the underlying measures.¹⁴ A summary of all the variables, in which each observation represents a single school in a single year, appears in Table 1. The number of applications is drawn from *Peterson's Guide to Competitive Colleges*.

3. Estimation Strategy

This section describes our estimation of whether rankings enter into applicants' demand functions and whether the salience of rankings matters. We first present the theoretical framework of the analysis, followed by the empirical identification strategies.

3.1 Conceptual Framework

Consider the demand function $x(q, r)$ faced by a college of quality q and rank r . In this setting, the semi-elasticity $\varepsilon_{x,r}$ represents the percentage change in the number of applicants that results from a one-rank improvement. This framework is similar to that used by Chetty et al. (2009), Finkelstein (2009), and Luca (2010). We focus on how elasticity is affected by salience. We denote a salient ranking as r^s and an opaque ranking as r^o . By definition, a salient ranking is one that is easily noticed by applicants, and an opaque ranking is one that students have to compute using the weights provided by USNWR. In the neoclassical full-optimization model, $\varepsilon_{x,r}$ would not be affected by whether the ranking is salient or opaque.

¹² Alumni-giving rank was introduced in 1993. Prior to that year, we enter a value of zero for all schools.

¹³ As noted, alumni-giving rank was added in 1993; freshman retention rate was included in retention and graduation rank in 1996.

¹⁴ Despite being included in the broad category rankings, USNWR does not publish average faculty salary, percentage of part-time faculty, or non-educational spending per student.

Our goal is to test the full-optimization neoclassical theory that $x(q, r^s) = x(q, r^o)$. Empirically, we do so in two steps. First, we estimate whether rankings do indeed have a causal impact on applications, such that demand is in fact a function of rankings. Second, we estimate $\varepsilon_{x,rs} - \varepsilon_{x,ro}$. The null hypothesis is that the neoclassical full optimization model holds and $\varepsilon_{x,rs} - \varepsilon_{x,ro} = 0$.

3.2 Identification Strategies

3.2.1 Causal Impact of Rankings

Our first objective is to test whether rankings have a causal impact on student choice. To do so, we must distinguish the impact of changes in a school's underlying quality from the impact of changes in the school's rank. Recall that a school's rank represents a weighted average of its performance on several dimensions of quality, and that the weights are chosen by USNWR. If the weights were constant over time, rank would be collinear with quality changes. However, USNWR changes the weights from year to year, making for plausibly exogenous variation in a school's rank. A complete list of methodology changes appears in Appendix B. Largely following Pope (2009), we exploit these USNWR methodology changes to pinpoint variation in rank with no underlying quality changes. This procedure allows us to estimate the causal impact of rankings on number of applications.

If students use only USNWR to obtain information about underlying school quality, we should see no response to rank once we control for the underlying categories. Let schools be indexed j and time be indexed t ; then this section's main specification for estimating demand is as follows:

$$x_{t+1}(q_{jt}, r_{jt}^s) = \alpha r_{jt}^s + \beta q_{jt} + J + T + \eta_{jt}$$

where $x_{t+1}(q_{jt}, r_{jt}^s)$ is demand measured by logarithm of number of applications in year $t+1$, and J and T are school and year fixed effects respectively, and η_{jt} is a school-year-specific idiosyncratic error term. Also, q_{jt} is the vector of broad categories in USNWR, or quality measures of school j . This section tests whether the coefficient on rank, α , is statistically different than zero. If we can reject the null hypothesis of $\alpha = 0$, then rank enters the demand for a school.

However, it is possible that quality measures are imperfectly measured, causing rank to be correlated with the error term. To control for this endogeneity, we take an instrumental variables approach. For years in which the formula changed, we use the previous year's methodology to predict rank in the absence of a methodology change. Then the difference between the predicted rank and the actual rank is calculated. This difference is untainted by changes in school quality that may be imperfectly controlled for in previous regressions. Using the difference to instrument

for actual rank will isolate out the portion of the rank change caused by the exogenous change in ranking methodology, as opposed to an improvement in school quality.

More formally, the instruments must satisfy the relevance condition and the exclusion restriction. The difference between predicted rank and actual rank certainly satisfies the relevance condition, as larger differences are associated with larger values of the potentially endogenous rank. The exclusion restriction is also likely to be satisfied because the difference between predicted and actual rank should have no effect on applications, other than via the endogenous variable. One potential violation of the exclusion restriction would occur if USNWR anticipated changes in student preferences and acted accordingly. However, though we exploit methodology changes to estimate the rank effect, the test for salience further reinforces the causal interpretation. In order for salience of rankings to have an effect, it must first be assumed that rankings have an effect and that this identification does not rely on exogenous methodology changes.

In addition to testing how rank affects the number of applications, we also test for its effect on acceptance rate, yield,¹⁵ average SAT of enrollees, and percentage of enrollees in the top 10 percent of their high-school class.

3.2.2 Salience

In this section, we aim to estimate the impact of salience of ranking on the elasticity of demand with respect to ranking. We use the 1995 expansion of rankings (from top 25 to top 50) as an identification strategy. Recall that in 1995 tier-2 schools (ranked 26-50), which had previously been listed alphabetically (opaque ranking), began to be explicitly ranked (salient ranking). Both before and after the methodology change, USNWR reported the weights assigned to each broad category; thus any applicant who thought that the weights conveyed meaningful information could have made use of them before 1995. Empirically, if salience of rank has an effect on applications, the demand elasticity with respect to rank should increase when rank becomes salient. Our identification strategy is to compare the demand elasticity before and after rank was explicitly listed for each school. We run several variants of this test to show that the result is robust to different specifications.

In an experimental setting, a test for salience would be immediate. We would simply provide the control group with the underlying categories and the weights to apply to each, which they could then use to construct rankings if they thought that doing so would be useful. We would provide the treatment group with the same information, but would also provide them the rankings so that they would not have to compute them themselves. Our market setting deviates from the experimental ideal in that USNWR publishes most but not all of the underlying categories. Specifically, it does not publish faculty resources, which is based on faculty salaries. The weights of multiple detailed sub-categories are also excluded. For instance, the broad category “selectivity rank” consists of acceptance rates and students’ high-school achievement,

¹⁵ Yield is the percentage of accepted students who choose to enroll.

but only the weight for “selectivity rank” is published, not the weights of the underlying information. Hence we must develop a test of salience that is robust to this shortcoming.

To construct rank prior to 1995, we regress tier-1 ranks on observable school data and use the coefficient estimates to impute rank.¹⁶ While this procedure deviates from the experimental ideal, our identification strategy leads to an unbiased estimated impact of salience. Essentially, any potential bias would arise from the fact that we are comparing the impact of estimated rankings in the opaque regime to actual rankings in the salient regime. To the extent that the actual rankings contain no noise while the estimated rankings contain noise, our estimated impact of salience would conflate the impact of salience with the impact of reducing measurement error. To eliminate this bias, we then use a consistent approach to estimating ranks for both the salient and opaque regimes. By introducing the same methodology (and hence the same measurement error) into the salient regime that is contained in the opaque regime, we increase the standard errors but are able to recover an unbiased estimate of how salience affects demand elasticity with respect to rank. We estimate the rankings by applying the category weights to the available data. This procedure shows what the rankings would be net of the missing data. After constructing hypothetical ranks, we eliminated all schools that had changed tiers (up or down) in 1994 just prior to the expansion of rankings.¹⁷ Doing so eliminates the possibility that students knew whether or not a school was on the cusp of a tier.¹⁸

Our first empirical test is to see whether the effect of rank on applications differs when it is salient from when it is opaque. To do so, we run a school and year fixed effects regression of logarithm of number of applications on rank and rank interacted with a salience indicator while controlling for underlying quality measures, including average SAT of enrollees, percentage in the top 10 percent of their high-school class, and graduation rate.¹⁹ A rank is defined as salient and equal to one when it is explicit and as equal to zero when listed alphabetically. The coefficient on the interaction term is testing the theoretical hypothesis that the elasticities of rank depend differently in the presence of saliency, or mathematically, $\varepsilon_{x,rs} - \varepsilon_{x,ro} \neq 0$.

This strategy may be problematic if the rank effect is larger for tier-1 schools than for tier 2. To show that this possibility is not driving our results, we restrict our attention solely to tier-2

¹⁶ We can also manually construct ranks using published weights for broad categories, and can try different sub-weights for data within broad categories. Running a regression produces similar results for rank.

¹⁷ We also try a more conservative estimate by dropping schools that jumped tiers anytime between 1990 and 1994. Because it seems unlikely that students look at the rankings so many years prior to their application year, we do not prefer this specification. Regardless, it does not qualitatively change results.

¹⁸ Tier-2 schools could be on the cusp of jumping either to tier 1 or to tier 3 (ranked above 50).

¹⁹ These underlying quality measures are heavily weighted and present in all years for tier-1 and tier-2 schools. Moreover, they are good proxies for school quality.

schools. Specifically, we look at how the elasticity with respect to rank changes for tier-2 schools after rank becomes salient. Again, the null is that $\varepsilon_{x,rs} - \varepsilon_{x,ro} = 0$.

A final issue with the identification strategy is that the impact of rank could be growing over time, which might cause elasticity to increase irrespective of salience. To control for a potential underlying trend in elasticity with respect to rank, we take a differences-in-differences approach.²⁰ Specifically, we test whether the elasticity $(\varepsilon_{x,r \text{ pre tier1}} - \varepsilon_{x,r \text{ post tier1}}) - (\varepsilon_{x,r \text{ pre tier2}} - \varepsilon_{x,r \text{ post tier2}}) = 0$.

4. Results

4.1 Rank Effect: Methodology Changes

Table 2 presents results from regressing logarithm of number of applications on rank and school-quality measures. Using the full sample for 1990-2000, OLS results show that a one-rank drop is associated with 0.96 percent fewer applicants. Even when changes in rankings reflect only methodology changes, applicants respond to a decline in rank.

To check the robustness of this result, the next two columns break the data into years with and without methodology changes. If the rank effect is driven by nonlinear responses to quality, the rank effect should appear in both sub-samples. In fact, however, there is no rank effect in years without methodology changes; there is a rank effect, estimated to be approximately -0.02, in the sub-sample with methodology changes. Since the full sample's estimate of rank effect is a weighted combination of these two sub-samples, it makes sense that the estimate is in between; the estimate is probably muted by the lack of identification in the years without methodology changes.

Table 3 shows results from instrumental variables. As shown, the coefficient on rank equals -0.0207 and is statistically significant. That this number is more than twice the size of the OLS result is not very surprising. Given the local average treatment effect interpretation, the schools that are most affected by methodology changes are those that exhibit larger changes in number of applications. Table 3 also presents the first stage.

Given the similarity of the sub-sample and instrumental variables, and accounting for issues in the full sample estimates, the true rank effect may be closer to 2 percent than to the OLS estimate of 0.96 percent. Moreover, all specifications yield the result that students consider rankings, beyond their informational content, when deciding where to apply to college.²¹

Looking at the USNWR rankings but not using this identification strategy, Monks and Ehrenberg (1999) and Bastedo and Bowman (2009) find a correlation between rankings and applications. This correlation is stronger for schools ranked 1-25 than for schools ranked 26-50. Using the same identification strategy in a hospital setting, Pope (2009) finds that an “average

²⁰ These methodologies estimate the effect of a change in salience on applications within a tier. Figure 1 demonstrates that there are no large shifts between tiers.

²¹ More flexible specifications, which allow for non-linearities in variables, are tested but not presented because the results are consistent with Tables 2 and 3.

hospital experiences a 5 percent change in non-emergency, Medicare patient volume from year to year due to rank changes.” Our first result is similar to this, but in an education setting.

4.1.1 Alternative Dependent Variables

Table 4 presents the same OLS and 2SLS regressions as Table 3 but uses several different outcome variables: acceptance rate, yield, average SAT of enrollees, and percentage of enrollees in the top 10 percent of their high-school class. The impact of rankings on acceptance rates is positive and significant. When a school increases in rank (ranked relatively worse), its acceptance rate increases. This result is consistent with the impact on the number of applications, since the denominator of acceptance rate is the number of applications. The remaining outcome variables attempt to characterize the composition of enrollees. There is no significant relationship between rankings and yield, average SATs, or percentage of enrollees in the top 10 percent of their high-school class.

Data availability limits our analysis of the quality of applicants: ultimately, average SAT and percent of students in the top 10 percent of their class are very coarse measures of quality. Hence we are cautious in interpreting these non-results.

4.1.2 Control Variables

Our estimation strategy allows us to identify the causal impact of rankings on applications, but does not allow us to identify the impact of underlying categories. The main explanation is that the underlying measures of quality could be correlated (positively or negatively) with other measures of quality that are observed by students but not by the econometrician. For example, one possible reason for the positive coefficient on faculty resources is that increases in faculty resources divert resources from other offerings that are of interest to applicants.

4.2 Salience: Expansion of Rankings

The first set of results on salience is presented in Table 5, which regresses logarithm of number of applications on rank, whether or not the ranking is salient, and the interaction of the two, while controlling for school and year fixed effects and several underlying quality measures. Method 1 estimates rank for tier-2 schools in 1990-1994, but uses the available rank for tier-1 and tier-2 schools after 1994. Method 2 uses estimates of rank for both tiers in all years.

In both specifications, the coefficient on rank is small and insignificant, but the interaction of salience and rank is estimated to be between -0.0082 and -0.0108. Moreover, a Wald Test on whether the sum of the two coefficients is different than zero can be rejected. Thus only when rankings are salient does a one-rank improvement lead to an increase of 0.55-0.71 percent in applications.²² Thus rank affects application decisions only when it is salient, a

²² These results are the sum of the two coefficients (e.g., $-0.0055 = -0.0082 + 0.0027$).

somewhat surprising finding given the magnitude of the decision about which college to attend. Appendices C-1 and C-2 shows the different ordering of tier 2 schools before and after the expansion, respectively.

Figure 2 provides supplemental graphical evidence on the role of salience. The figure presents year-by-year coefficients for the impact of rank on applications for both tiers. While the coefficients are noisy (since they greatly reduce the number of observations), they do show that the effect of rankings is fairly constant over time for tier 1, while the impact grows for tier 2 once the rankings are displayed.

The remaining results show the robustness of the salience effect. Table 6 again estimates the impact of salience but only includes tier-2 schools, which are subject to the regime change. Using the same two methods to construct rank, again only salient rankings affect application decisions. The strongly negative and significant coefficient on rank and an indicator for whether rankings are salient is between -0.0074 and -0.0103. Hence, when the rank is opaque, it has no impact; however, a one-rank improvement increases applications by approximately 0.8 percent when the ranking is salient.

Table 7 uses a differences-in-differences approach to make sure that the salience result in Table 6 is not being driven by an underlying trend in responsiveness to rank. In this case, tier 2 is compared to tier-1 schools over the two time periods. Supporting the salience hypothesis, rank only matters when it is visible alongside the underlying data and methodology. In both specifications, salience increases demand elasticity by at least 0.72.

Our interpretation of these results is that applicants responds to the salience of the rankings. An alternative explanation is that colleges are more likely to compete for applications when faced with salient rankings. However, Section 4.1 demonstrates that students are responsive to rankings, even when there was no change in the salience of the rankings. This evidence suggests that students are at least partially responsible for an increase in applications to highly ranked colleges once the rankings are salient. Colleges may also change their behavior due to the salience of rankings, which is beyond the scope of this paper.

This section has shown that the elasticity of demand with respect to a school's rank is determined almost exclusively by the salience of that rank. We firmly reject the hypothesis that how quality information is displayed has no impact on the elasticity. The null hypothesis is rejected for at least one quality dimension of one of the largest purchases many people make. This finding adds to our understanding of salience, by showing that salience matters not just with regard to prices and taxes, but also to understanding the quality of a good. It also shows that salience matters in very large one-time purchases, which is precisely where the literature has cast doubt.

In our setting, as well as the tax setting, these salience effects occur when information is more visible to decision-makers. In our paper, as well as Chetty (2009), salience is defined in terms of the cost of processing information. Hence, applying weights to information makes it

more salient. In contrast with the tax case, however, it is unclear how information *should* be aggregated in the college choice problem. We abstract from this issue in our paper.

5. Discussion

This paper has presented two main findings. First, *U.S. News and World Report* College Rankings has a causal impact on application decisions. Second, the demand elasticity with respect to the rankings is affected by the salience of the ranking. These findings contribute to two separate strands in the literature. First, they enrich the literature on the effects of the USNWR College Rankings. The existing literature has shown a strong correlation between rankings and demand, but our findings provide further support for the hypothesis that these rankings have a causal impact on students' application decisions. Second, this paper contributes to the literature on salience. Conventional wisdom to the contrary, salience has a large effect on one of the largest investments most people make in their lifetimes, namely where they choose to go to college.

This paper has several limitations, which we hope will be addressed in future research.

5.1 Limitations and Future Research

We have isolated the causal effect of USNWR, and shown that the response differs depending on how information is presented. One limitation of this paper is that we do not fully address why students rely on rankings. Rankings may serve as a simplifying tool for applicants, reducing the time and effort required to sort through the pertinent information, or even providing guidance on which information is important. However, rankings could have an effect even if the underlying information were not important. Specifically, students may choose a highly ranked school primarily in order to signal their ability.

Understanding which of these two mechanisms is most relevant is important from both a policy and an information-design perspective. If rankings are primarily a simplification tool, the choice of weights is critical from a policy perspective; incorrect weights could lead to severe welfare losses. If, on the other hand, rankings simply help students signal their ability, the choice of weights is unimportant—any arbitrary set of weights could enable students to coordinate with future employers. Though beyond the scope of this paper, this is a promising area for future research.

Another limitation of this paper is that we have not observed how students learn about the rankings. Many students clearly read USNWR, but schools also use their rankings in advertisements and as a marketing device. This phenomenon might play a non-trivial role in amplifying the rank effect by increasing the visibility of rankings to students. We are unable to distinguish these effects. Future research could investigate this question and, more generally, the information-revelation strategies of universities.

Finally, we have only briefly mentioned the supply-side effects of rankings and these results. Since rankings affect applications, colleges have an incentive to improve their rank. Moreover, improved rankings increase applications, which lowers acceptance rates and in turn,

improves rankings. Rankings may therefore provide incentives for colleges to reallocate of resources. We abstract from these supply-side incentives but view this as promising future research.

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Table 1. Summary Statistics

<u>Variable</u>	<u>Mean</u>	<u>Std.Dev.</u>	<u>Min</u>	<u>Max</u>
<i>Top 25 Schools, 1990-2000 (256 obs)*</i>				
Rank	12.6	7.8	1	33
Reputation Rank	12.2	9.5	1	55
Selectivity Rank	14.8	11.1	1	54
Faculty Resource Rank	18.9	16.8	1	97
Retention and Graduation Rank	17.0	13.2	1	72
Financial Resource Rank	17.9	14.3	1	64
Alumni Giving Rank**	31.1	35.1	1	165
Number of Applications	12,597	5,758	1,173	35,681
<i>Top 50 Schools, 1990-2000 (485 obs)***</i>				
Number of Applications	11,859	5,612	1,561	32,539
Average SAT	1,267	105	1,015	1,515
Top 10% of High-School Class	72	18	30	100
Acceptance Rate	46	20	11	88
Graduation Rate	81	11	47	97

*As determined by 1990 rankings.

**Only 187 observations, because the variable was not introduced until 1993.

***Because this category includes only schools consistently ranked in the top 25 or consistently

**Table 2. Rank Effect: Regressions on Quantity of Applicants, Top 25 Schools
USNWR College Rankings, 1990-2000**

Dependent Variable = log (# of applications)

<u>Variable</u>	<u>Full Sample</u> <u>1990-2000</u>	<u>No Method Changes</u> <u>1996-1998</u>	<u>Method Changes</u> <u>1991-1994</u>
Rank	-0.0096** (0.0041)	0.0030 (0.0080)	-0.0187** (0.0071)
Reputation Rank	-0.0045 (0.0034)	-0.0031 (0.0064)	0.0055 (0.0043)
Selectivity Rank	-0.0184*** (0.0020)	-0.0124 (0.0093)	-0.0054 (0.0036)
Faculty Resource Rank	0.0021*** (0.0007)	-0.0016 (0.0016)	0.0041*** (0.0010)
Retention and Graduation Rank	-0.0002 (0.0015)	-0.0115 (0.0077)	0.0095*** (0.0034)
Financial Resource Rank	-0.0012 (0.0018)	0.0005 (0.0038)	-0.0015 (0.0031)
Alumni Giving Rank	-0.0005 (0.0004)	-0.0009 (0.0010)	0.0007* (0.0004)
Observations	258	71	92
R-squared	0.976	0.992	0.991
Note: Robust standard errors in parentheses. * = significant at 10% level, ** 5% level, and *** 1% level. Regression also controls for year and school fixed effects.			

**Table 3. Rank Effect: Regressions on Quantity of Applicants, Top 25 Schools
USNWR College Rankings, 1990-2000**

Dependent Variable = log (# of applications)

<u>Variable</u>	<u>OLS</u>	<u>IV</u>
Rank	-0.0096** (0.0041)	-0.0207*** (0.0058)
<i>First-Stage Results</i>		
Difference between Rank and Rank with previous year's methodology ¹	-- --	0.5887*** (0.0528)
Observations	258	258
R-squared	0.976	0.975
First-Stage F-Statistic	--	642.71
<p>Note: Robust standard errors in parentheses. * = significant at 10% level, ** 5% level, and *** 1% level. Regression also controls for underlying categories and year and school fixed effects. 1. Rank with previous year's methodology is predicted.</p>		

**Table 4. Rank Effect: Regressions on Quantity of Applicants, Top 25 Schools
USNWR College Rankings, 1990-2000
Alternative Dependent Variables**

Variable	<i>Dependent Variable</i>									
	<i>Log (# of applications)</i>		<i>Acceptance Rate</i>		<i>Yield</i>		<i>SAT</i>		<i>Top 10% in High-School Class</i>	
	<i>OLS</i>	<i>IV</i>	<i>OLS</i>	<i>IV</i>	<i>OLS</i>	<i>IV</i>	<i>OLS</i>	<i>IV</i>	<i>OLS</i>	<i>IV</i>
Rank	-0.0096** (0.0041)	-0.0207*** (0.0058)	0.0133** (0.0057)	0.0344*** (0.0086)	-0.0877 (0.1414)	-0.2086 (0.1575)	-0.3914 (0.5163)	-0.2758 (0.8696)	0.0377 (0.1316)	0.1649 (0.1801)
<i>First-Stage Results</i>										
<i>Instrument</i>										
Difference between Rank and Rank with previous year's methodology ¹	--	0.5939*** (0.0547)	--	0.5905*** (0.0523)	--	0.5967*** (0.0526)	--	0.5927*** (0.0525)	--	0.5905*** (0.0523)
Observations ²	258	258	259	259	248	248	258	258	259	259
R-squared	0.976	0.975	0.934	0.929	0.959	0.958	0.980	0.980	0.944	0.944
First Stage F-Statistic	--	642.71	--	642.65	--	794.04	--	629.53	--	642.65

Note: Robust standard errors in parentheses. * = significant at 10% level, ** 5% level, and *** 1% level. Regression also controls for underlying categories and for year and school fixed effects. Instruments are the difference between predicted rank using previous year's methodology and actual rank.

1. Rank with previous year's methodology is predicted.

2. Numbers of observations differ because some college data was not published in some years.

Table 5. Salience
USNWR College Rankings, Top 50 Schools
Expansion of Rankings

Dependent Variable = log (# of applications)

<u>Variable</u>	<u>Method 1</u>	<u>Method 2</u>
Salient x Rank	-0.0108*** (0.0028)	-0.0082*** (0.0025)
Rank	0.0037 (0.0023)	0.0027 (0.0025)
Observations	468	467
R-squared	0.955	0.954
Wald Test p-value (Rank + Salient x Rank = 0)	0.0004	0.0132

Notes: Results from OLS regressions using data from 1990-2000. Salient x Rank implies that rank was shown explicitly, not listed alphabetically. Second-tier schools were ranked 26-50 in 1995. Method 1 estimates second-tier ranks from 1990-1994 but uses actual rank for all other schools. Method 2 estimates all rankings from 1990-2000. Estimated ranks use OLS regression of Rank on school characteristics. School and year fixed effects are included, as are controls for school quality that are present in all years. Robust standard errors in parentheses. * = significant at 10% level, ** 5% level, and *** 1% level.

Table 6. Salience
USNWR College Rankings, Tier-2 Schools
Pre/Post Expansion

Dependent Variable = log (# of applications)

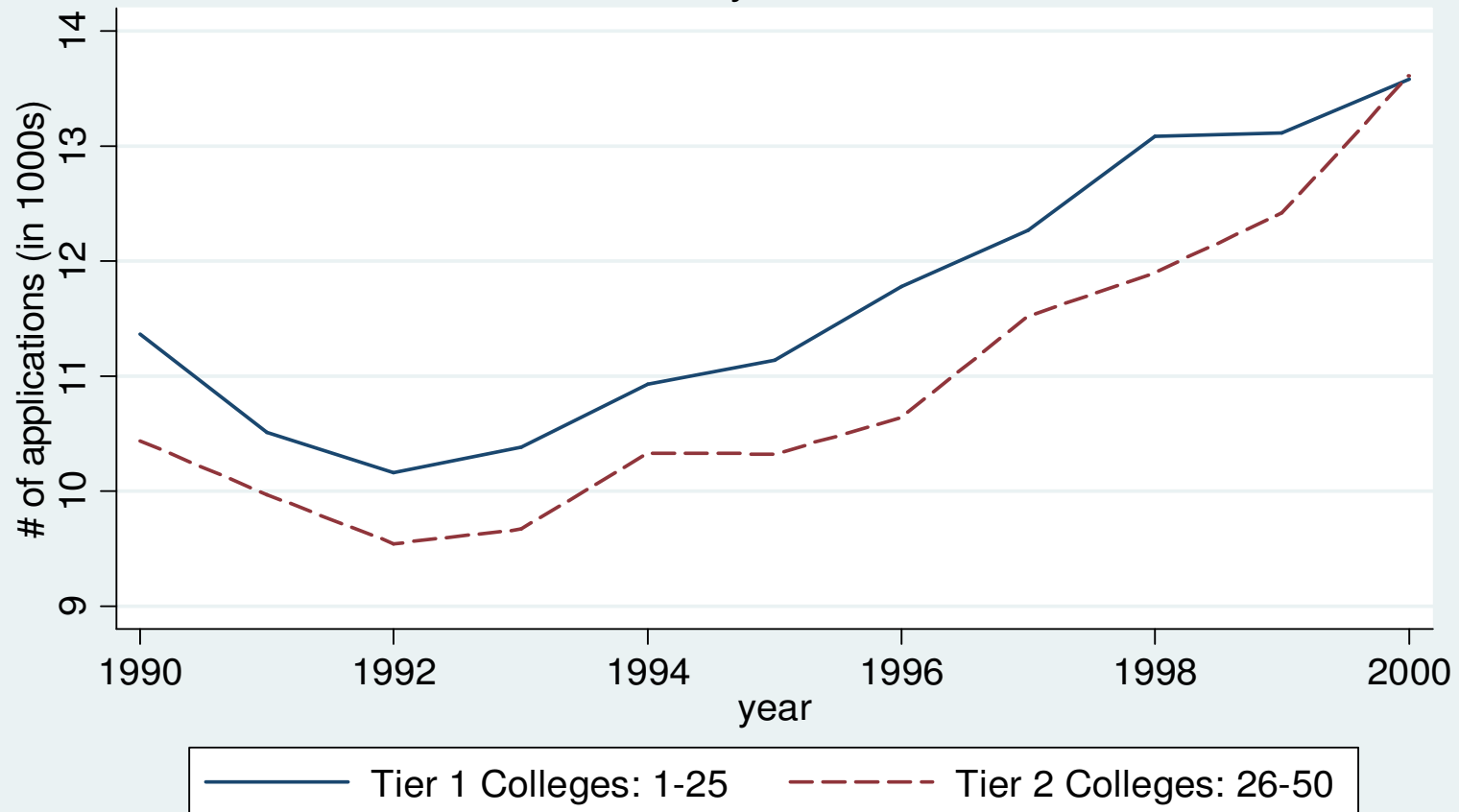
<u>Variable</u>	<u>Method 1</u>	<u>Method 2</u>
Salience Effect: Post 1994 x Rank	-0.0103*** (0.0032)	-0.0074*** (0.0028)
Rank	0.0018 (0.0026)	-0.0008 (0.0031)
Observations	216	215
R-squared	0.943	0.942
Wald Test p-value (Rank + Salience Effect = 0)	0.0019	0.0123

Notes: Results from OLS regressions. Salient Effect implies that rank was shown explicitly, not listed alphabetically. Second-tier schools were ranked 26-50 in 1995. Method 1 estimates second-tier ranks from 1990-1994 but uses actual rank for all other schools. Method 2 estimates all rankings from 1990-2000. Estimated ranks use OLS regression of Rank on school characteristics. School and year fixed effects are included, as are controls for school quality that are present in all years. Robust standard errors in parentheses. * = significant at 10% level, ** 5% level, and *** 1% level.

Table 7. Salience
USNWR College Rankings, Top 50 Schools
Expansion of Rankings, Differences-in-Differences
Dependent Variable = log (# of applications)

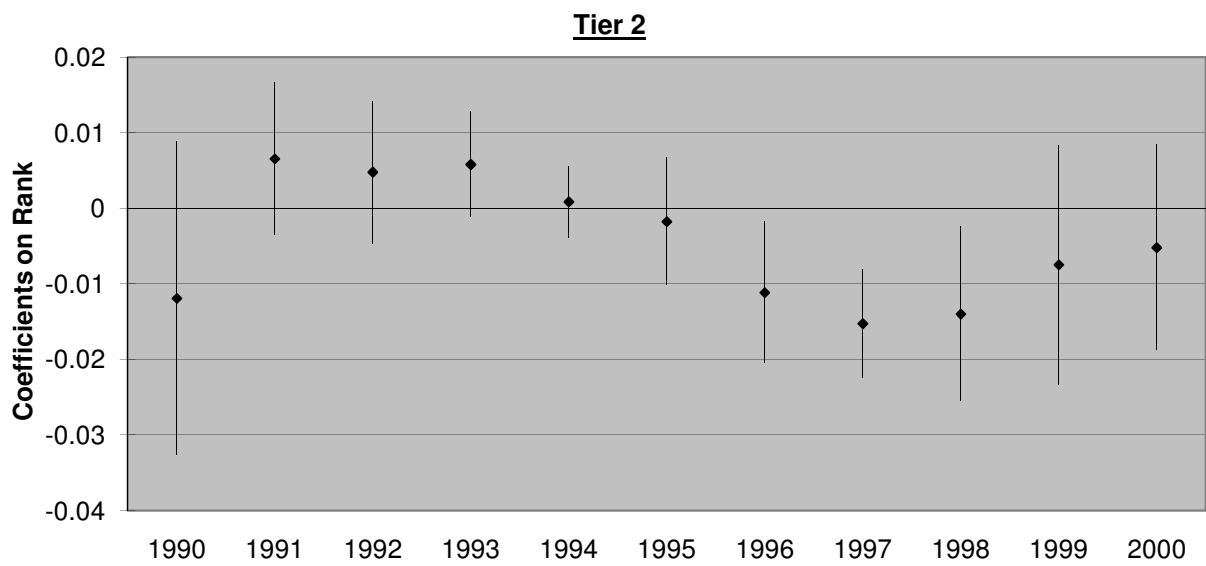
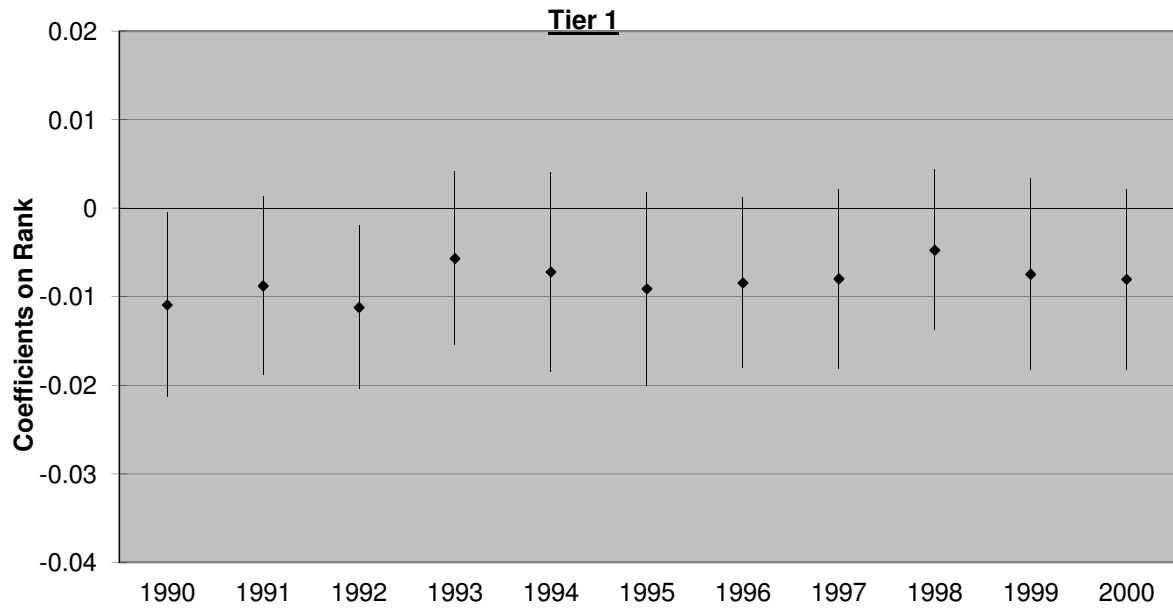
<u>Variable</u>	<u>Method 1</u>	<u>Method 2</u>
Salience Effect: Post-1994 x Second Tier x Rank	-0.0090*** (0.0029)	-0.0072*** (0.0027)
Rank	0.0002 (0.0018)	-0.0001 (0.0020)
Second Tier	2.5830*** (0.1194)	-0.3335*** (0.0363)
Post 1994 x Second Tier	0.3451*** (0.1104)	0.2722*** (0.1033)
Observations	468	467
R-squared	0.954	0.954
Wald Test p-value (Rank + Salience Effect = 0)	0.0008	0.0106
<p>Notes: Results from OLS regressions. Salient Effect implies that rank was shown explicitly, not listed alphabetically. Second-tier schools were ranked 26-50 in 1995. Method 1 estimates second-tier ranks from 1990-1994 but uses actual rank for all other schools. Method 2 estimates all rankings from 1990-2000. Estimated ranks use OLS regression of Rank on school characteristics. School and year fixed effects are included, as are controls for school quality that are present in all years. Robust standard errors in parentheses. * = significant at 10% level, ** 5% level, and *** 1% level.</p>		

Figure 1: Average Number of Applications Over Time
By Tier*



*Tiers determined by 1995 rankings

**Figure 2: Coefficient Estimates of Rank Effect on Applications
By Year and Tier
Point Estimate and 95% Confidence Interval**



Appendix A: Top 50 Schools in 1995, USNWR

Ranked 1-25

Brown University*
 California Institute of Technology*
 Carnegie Mellon University*
 Columbia University*
 Cornell University*
 Dartmouth College*
 Duke University*
 Emory University
 Georgetown University*
 Harvard University*
 Johns Hopkins University*
 Massachusetts Institute of Technology*
 Northwestern University*
 Princeton University*
 Rice University*
 Stanford University*
 Tufts University
 University of Chicago*
 University of Michigan--Ann Arbor*
 University of Notre Dame
 University of Pennsylvania*
 University of Virginia*
 Vanderbilt University
 Washington University in St. Louis*
 Yale University*

Ranked 26-50

Boston College
 Brandeis University
 Case Western Reserve Univ.
 College of William and Mary
 Georgia Institute of Technology
 Lehigh University
 New York University
 Pennsylvania State University--University Park
 Rensselaer Polytechnic Institute
 Rutgers New Brunswick
 Syracuse University
 Tulane University
 University of Illinois--Urbana-Champaign
 University of North Carolina--Chapel Hill*
 University of California--Los Angeles
 University of California--San Diego
 University of Southern California
 University of Wisconsin--Madison
 University of California--Berkeley*
 University of California--Davis
 University of California--Irvine
 University of Florida
 University of Rochester*
 University of Washington
 Wake Forest University

*Among the top 25 in 1990 rankings.

Appendix B. Changes in Methodology (1990-2000)

(Items in bold indicate methodology change)

<u>Year</u>	<u>Reputation</u> <u>Rank</u>	<u>Selectivity</u> <u>Rank</u>	<u>Faculty</u> <u>Resource</u> <u>Rank</u>	<u>Retention</u> <u>and</u> <u>Graduation</u> <u>Rank</u>	<u>Financial</u> <u>Resource</u> <u>Rank</u>	<u>Alumni</u> <u>Giving</u> <u>Rank</u>
1990	25	25	25	5	20	0
1991	25	25	25	5	20	0
1992	25	25	25	7	18	0
1993	25	25	20	10	15	5
1994	25	25	20	15	10	5
1995	25	15	20	25	10	5
1996	25	15	20	25*	10	5
1997	25	15	20	25	10	5
1998	25	15	20	25	10	5
1999**	25	15	20	25	10	5
2000	25	15	20	25	10	5

**Prior to 1996, only graduation rate was considered. In 1996, the weighting of graduation rate decreased to 20% and retention rank was assigned a weight of 5%.*

***Rather than ranking the schools in each subcategory and then weighting each rank, the top school in each category was assigned a score of 100% and other schools were assigned scores relative to it, which were then summed.*

APPENDIX C-1

USNWR – 1994

	Avg./midpt. SAT/ACT score	SAT/ACT 25-75 percentile	Fresh. in top 10% of HS class	Acceptance rate	Faculty with Ph.D.	Student/faculty ratio	Educ. program per student	Alumni giving rate	Grad. rate	Academic reputation rank
TIER ONE / SCHOOLS RANKED 26TH TO 57TH										
Boston College (MA)	1210	1120-1300	66%	47%	95%	17 1	\$10.989	27%	87%	65
Boston University (MA)	1150	1050-1250	45%	64%	81%	16 1	\$16.836	16%	69%	58
Brandeis University (MA)	1215	1100-1330	48%	66%	97%	10 1	\$17.150	24%	81%	42
Case Western Reserve University (OH)	1235	1090-1380	71%	81%	95%	10 1	\$19.733	29%	65%	42
College of William and Mary (VA)	1240	1130-1350	68%	44%	92%	12 1	\$9.534	31%	90%	37
Colorado School of Mines	1200	1075-1325	65%	81%	95%	14 1	\$11.838	22%	78%	76
Georgia Institute of Technology	1240	1150-1330	89%	58%	92%	19 1	\$11.271	33%	68%	31
Lehigh University (PA)	1140	1030-1250	40%	67%	99%	13 1	\$14.665	43%	88%	76
New York University	1145	1040-1250	70%	53%	98%	11 1	\$21.227	16%	69%	51
Penn State Univ. at Main Campus	1096	980-1211	48%	54%	96%	18 1	\$8.992	19%	61%	31
Pepperdine University (CA)	1070	960-1180	86%	53%	98%	11 1	\$16.185	13%	64%	107
Rensselaer Polytechnic Institute (NY)	1190	1080-1300	53%	83%	98%	15 1	\$15.605	21%	68%	51
Rutgers at New Brunswick (NJ)	1110	990-1230	36%	55%	95%	20 1	\$10.474	19%	74%	42
SUNY at Binghamton	1150	1050-1250	60%	43%	100%	18 1	\$8.055	15%	77%	83
Tufts University (MA)	1240	1150-1330	60%	47%	100%	14 1	\$18.981	22%	89%	51
Tulane University (LA)	1168	1050-1286	47%	72%	98%	13 1	\$16.920	21%	71%	51
University of California at Davis	1075	940-1210	95%	70%	98%	22 1	\$15.873	11%	73%	42
University of California at Irvine	1025	900-1150	85%	69%	96%	20 1	\$15.934	11%	64%	58
Univ. of California at Los Angeles	1154	1018-1290	93%	47%	99%	19 1	\$20.260	9%	74%	21
University of California at San Diego	1135	1020-1250	95%	59%	100%	22 1	\$17.674	6%	64%	42
Univ. of California at Santa Barbara	1010	920-1100	90%	85%	100%	19 1	\$9.475	6%	66%	65
University of Florida	1135	1020-1250	54%	71%	97%	19 1	\$14.737	20%	64%	42
Univ. of Illinois at Urbana-Champaign	1150	1020-1280	52%	78%	90%	18 1	\$8.559	13%	78%	21
University of Iowa	25	22-27	23%	87%	98%	22 1	\$12.194	37%	60%	37
University of Minnesota at Twin Cities	1060	920-1200	26%	58%	90%	17 1	\$16.122	37%	43%	26
Univ. of North Carolina at Chapel Hill	1045	990-1100	75%	41%	93%	14 1	\$15.893	23%	81%	16
University of Rochester (NY)	1140	1020-1260	56%	63%	99%	13 1	\$26.037	23%	77%	51
University of Southern California	1090	950-1230	45%	69%	94%	14 1	\$17.007	10%	66%	42
University of Texas at Austin	1135	1012-1258	48%	65%	99%	20 1	\$7.837	11%	62%	21
University of Washington	1055	920-1190	40%	55%	94%	13 1	\$16.527	10%	62%	26
University of Wisconsin at Madison	1085	940-1230	36%	73%	96%	15 1	\$11.006	20%	69%	16
Wake Forest University (NC)	1250	1150-1350	75%	42%	97%	13 1	\$41.766	37%	86%	76

APPENDIX C-2

USNWR – 1995

Rank/School name (State)	Overall score	SAT/ACT 25th-75th percentile	Percentage in top 10% of HS class	Acceptance rate	Yield	Student/faculty ratio	Expend. per student	Four-year retention rate	Graduation rate	Alumni giving rate	Reputation
SCHOOLS RANKED 26TH TO 50TH											
26. University of California at Berkeley	86.4	1110-1370	95%	40%	40%	17/1	\$15,140	93%	78%	10%	4
27. Univ. of North Carolina at Chapel Hill	86.1	1010-1250	72%	39%	57%	15/1	\$17,284	94%	83%	23%	20
28. University of California at Los Angeles	84.6	1000-1270	93%	50%	35%	20/1	\$20,241	94%	76%	15%	20
29. University of Rochester (N.Y.)	84.0	1020-1250	49%	63%	22%	13/1	\$28,299	93%	77%	27%	49
30. Brandeis University (Mass.)	82.4	1130-1340	48% ³	68%	27%	10/1	\$17,371	89%	81%	26%	43
31. Wake Forest University (N.C.)	81.9	1150-1350	68%	44%	36%	9/1	\$46,622	93%	85%	38%	73
32. University of Wisconsin at Madison	81.2	940-1230	40%	69%	45%	15/1	\$11,857	91%	71%	20%	17
33. Lehigh University (Pa.)	80.3	1025-1240	42%	64%	26%	13/1	\$15,226	91%	87%	52%	73
34. College of William and Mary (Va.)	79.9	1120-1340	70%	40%	40%	12/1	\$10,172	94%	90%	33%	36
35. Case Western Reserve University (Ohio)	79.6	1110-1380 ³	69%	81%	22%	13/1	\$20,672	92%	67%	28%	49
36. New York University	78.6	1055-1255	60%	52%	38%	14/1	\$23,242	86%	69%	18%	43
37. Boston College	78.1	1120-1300	66%	41%	35%	17/1	\$11,628	93%	88%	27%	64
38. Tulane University (La.)	77.9	1070-1290	42%	73%	21%	14/1	\$17,835	85%	73%	22%	49
39. Rensselaer Polytechnic Institute (N.Y.)	77.5	1070-1300	56%	88%	23%	17/1	\$15,536	87%	70%	21%	49
40. University of California at Davis	77.1	930-1200	95%	70%	27%	24/1	\$15,905	91%	74%	9%	36
41. Penn State Univ. at Main Campus	77.0	960-1201	38%	54%	35%	18/1	\$10,185	93%	80%	20%	27
42. Georgia Institute of Technology	76.9	1170-1330	90%	59%	38%	19/1	\$12,128	86%	69%	34%	27
43. University of California at San Diego	76.2	980-1240	95%	64%	22%	23/1	\$18,668	93%	68%	6%	43
44. University of Southern California	75.7	1000-1230	40%	72%	28%	15/1	\$17,822	89%	67%	12%	36
45. Rutgers Univ. at New Brunswick (N.J.)	74.4	960-1220	35%	55%	17%	19/1	\$11,027	90%	75%	18%	49
45. Univ. of Illinois at Urbana-Champaign	74.4	23-28	50%	76%	48%	18/1	\$8,515	91%	79%	14%	20
47. University of Florida	73.4	980-1220	60%	64%	41%	19/1	\$16,638	89%	64%	17%	43
48. University of California at Irvine	72.4	890-1140	85%	73%	24%	21/1	\$16,191	92%	69%	11%	49
49. Syracuse University (N.Y.)	72.0	990-1220	33%	67%	38%	11/1	\$14,813	88%	70%	19%	64
50. University of Washington	71.6	920-1190	40% ³	61%	48%	14/1	\$15,632	91%	64%	10%	27