The Robustness of the Graduation Rate Performance Indicator Used in the U.S. News & World Report College Rankings

Stephen R. Porter

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Abstract

This paper analyzes the robustness of the U.S. News graduation rate performance indicator, calculated as the difference between an institution’s actual graduation rate and their predicted graduation rate from a linear regression equation controlling for student aptitude and institutional expenditures. Robustness is examined in four areas: the effect of small changes in the sample due to missing data or changes in how the sample of national universities is defined; the effect of seemingly irrelevant changes in variable definition; the effect of different model specifications that take into account additional measures of student quality and institutional constraints, and how the use of confidence intervals for the predicted values changes conclusions about performance. Changes in the sample and variable definitions can cause the predicted graduation rate for an institution to fluctuate by plus or minus two percentage points. More refined model specifications reduce the number of institutions with extreme performance differences and can actually change an institution from underperformance to overperformance, or vice versa. Finally, the use of confidence intervals for the predicted graduation rates reveals that only about 5 percent of the institutions in this study have a predicted graduation rate that significantly differs from their actual graduation rate. The implications of these findings for these types of models, and recommendations for future research, are discussed.

Keywords: college rankings, US News & World Report, graduation rates

Introduction

College rankings have become a permanent fixture in higher education,
with *U.S. News & World Report* (USN) annual rankings having achieved prominence in the United States. The popularity (as well as the critiques) of college rankings is also growing outside the United States. *Maclean’s* magazine, for example, now combines institutional data with survey data in a process to rank Canadian universities.¹

These rankings can have a large impact on admissions and fund-raising. One national study of college freshmen in the USA found that 40 percent of students find college rankings somewhat or very important, with this proportion much higher for high-achieving students.² Strong performance in the rankings can also affect fund-raising—Berea College, for example, received a $25,000 donation from a nonalumnus after the ensuing publicity over their strong showing in the USN rankings.³

Given the immense publicity that these rankings create, and the impact of a positive or negative outcome on admissions and advancement, it is crucial to understand exactly how these rankings are derived. While the creators of these rankings have slowly become more open about their construction, research into how these rankings are constructed and the impact of various formulations on how institutions are rated is limited.⁴ This paper looks at one component of USN’s college rankings, their graduation rate indicator.

The Graduation Rate Indicator

USN attempts to determine “America’s best colleges” through their controversial annual college rankings.⁵ These rankings are based on several different items, each attempting to measure some important aspect of institutional quality. One item, graduation rate performance (formerly referred to by USN as value added), “...is designed to capture the effect of the college’s programs and policies on the graduation rate of students after controlling for spending and student aptitude, which also affect graduation rates.”⁶ After regressing the actual six-year graduation rate for a new freshman cohort on both the average SAT score for the cohort and the amount of money spent by the institution per student, USN uses the statistical results to calculate a predicted six-year graduation rate for the institution. This rate is an estimate of what the institution’s graduation rate should be, given the quality of its students and institutional expenditures. The difference between the actual and predicted rates yields the performance indicator, so that “If the actual graduation rate is higher than the predicted rate, the college is enhancing the students’ achievement.”⁷

This indicator is an intuitively appealing input-output model: after controlling for student input (quality of the freshman cohort) and the constraints faced by the institution (the amount of money they are able to spend), one can easily determine what the output should be. If the actual output differs, we have some measure of how institutional policies such as faculty-student ratios, class size, and so forth, affect student behavior (graduation within six years). USN uses this approach to publish differences between expected and actual graduation rates for individual institutions, which they refer to as overperformance or underperformance. Fig. 1 presents the distribution of the actual 1997 graduation rates by their predicted rates listed in the 1998 rankings for the USN sample of national universities. The national universities appear quite well they graduate their one-quarter of the sample,

![Figure 1: Actual and Predicted Graduation Rates](image)

The USN indicator is one approach in a growing body of literature attempting to assess institutional performance. Alexander, Higher Education Research has advocated a similar method of estimating graduation rates. The National Graduation Rate Study conducted within the A
universities appear quite varied in how well they graduate their students. Over one-quarter of the sample have predicted graduation rates that are ten percentage points higher or lower than their actual graduation rates (the maximum positive difference is +35 and the maximum negative is -19).

The USN indicator is simply one approach in a growing area of research attempting to assess institutional performance. Alexander Astin of the Higher Education Research Institute has advocated a similar methodology for estimating graduation rates, as has the National Graduation Rate Study conducted within the American Association of Universities and the Postsecondary Education Opportunity newsletter. (The main differences between these studies have been the number and type of independent variables used to estimate predicted graduation rates and the time-to-degree used to calculate the dependent variable. In addition, the Astin and Howard et al., studies use individual level data. The critiques in this paper apply equally to these studies.) These measures have undoubtedly been spurred in part by the growing demand in accountability from state and federal lawmakers. While this type of assessment is certainly a worthy goal, this paper contends that researchers in this area have
been on a fool's errand: it is simply
impossible to use these methodologies
claim that an individual institution is
overperforming or underperforming in
any meaningful way.

To understand the reason behind this
conclusion one must first understand
the two main purposes of estimating statistical
models in the social sciences. By far the
most common purpose has been
hypothesis testing: does an individual
variable have an impact on the
phenomenon under study? The second
purpose has been prediction: how does the
phenomenon under study change for an
individual observation given changes in
the predictor variables? The results of a
hypothesis test in a good model are
usually stable given small changes in the
data because standard hypothesis tests
generally yield a yes/no answer based on
the size of the coefficient and other
information about the sample. The
individual predictions for each
observation, however, are not necessarily
stable, since the predicted value is not a
binary outcome but is instead an actual
number. Changes in the estimated
coefficients that would not affect the
results of a hypothesis test may have large
effects on the predicted values for an
individual observation. Herein lies the
flaw in these regression studies: small
changes in sample selection, variable
definition, and model specification can
yield large changes in predictions.

In addition, these studies fail to take
into account the nature of the predicted
values taken from the regression equations
that are used to calculate the predicted
graduation rates. These values are an
economic forecast from an error-based
statistical model, and as such contain
error themselves. Confidence intervals
should be reported for these forecasts to
take this factor into account (similarly,
public opinion polls reported on the
evening news also report confidence
intervals in the form of “60 percent of the
American people support policy X, plus or
minus three percentage points”). As will
be seen, these confidence intervals often
bracket the actual graduation rates for
many institutions, yielding the conclusion
that the predicted rates do not
significantly differ from the actual rates.
Yet USN and other researchers report
these institutions as overperformers or
underperformers, while the models
themselves indicate they are performing as
expected.

The data used in this study are very
similar to the data used in the most recent
USN rankings for national universities.\textsuperscript{12}
The remainder of the paper assesses the
robustness of the graduation rate
performance approach by examining four
potential problem areas:

- Small changes in the sample due to
missing data or changes in how the
sample of national universities is
defined.
- Seemingly irrelevant changes in variable
definition.
- Different model specifications that take
into account additional measures of
student quality and institutional
constraints.
- Confidence intervals for the predicted
values.

**Robustness of the Predicted Graduation Rates**

**Sample Selection**

Although not discussed in the graduation
rate literature, changes in the sample of
universities may have had an impact on the
inguessed performance of an individual
institution. A robustness check of the
graduation rate performance estimates may
be impacted by the change in sample
universities. Although not immune to such
changes, it is possible that the
methodology for estimating
graduation rates may have been impacted
in the sample used to estimate graduation
rates for national universities. As a
result, the inclusion of more
universities may have impacted the
estimates. This impacts the
estimates in a way that may
be difficult to detect.

**Confidence Intervals**

Confidence intervals are used to
provide a range of values for the
predicted graduation rate estimates. These
intervals are calculated based on the
sample used to estimate the
graduation rate estimates. As
the sample size increases, the
confidence intervals become
narrower, providing a more
precise estimate of the
predicted graduation rate.

**Variable Definition**

Changes in the definition of
variables used to estimate
graduation rates may impact
the estimated graduation
rates. For example, changes in
the definition of “national
universities” may impact the
estimated graduation rates for
national universities.

**Model Specification**

Changes in the model specification
may impact the estimated
graduation rates. For example,
changes in the model specification
may impact the estimated
classification of institutions as
overperformers or
underperformers.

**Conclusion**

The results of this study suggest that
changes in the sample of
universities, changes in variable
definition, and changes in model
specification may impact the
estimated graduation rates. As
a result, the estimated
graduation rates should be
interpreted with caution.
These forecasts to judgment (similarly, 95 percent of the unit confidence intervals contain 90 percent of the data), as will 95 percent of the intervals often used for as a measure of the actual rates. As will 95 percent of the intervals often used for 95 percent of the intervals often used for

In the most recent rankings of institutional universities, the institutions are performing at an all-time peak. The study is so

of the sample is due to the fact that in how the sample is selected. The universities is the measure of the predicted

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The Robustness of the Graduation Rate Performance Indicator

institutions may have an impact on how well an individual university is estimated to perform. A robust measure of
graduation rate performance should be immune to such changes: if small changes in the sample causes the measure to fluctuate, it becomes difficult to defend any conclusion of overperformance or underperformance. Two factors may cause the sample to change. First, there may be missing data for some variables or for entire institutions. This is a common occurrence in national studies attempting to collect data from numerous universities. Second, the institutions used in these studies are defined to be "national" universities, with the implication that universities can gain or lose national status over time and thus change the makeup of the sample.

A close examination of the latest USN rankings shows that several institutions have a "N/A" reported for their predicted graduation rates. For example, Union Institute in Ohio does not have a predicted graduation rate reported in the 1999 rankings. An examination of the 1992 rankings reveals that SAT scores were not reported by USN for that year, so it is likely that USN was unable to collect SAT scores for Union Institute's Fall 1991 cohort. (USN confirms that institutions are excluded based on a lack of historical data. The reason behind some of the other N/As, however, is a mystery. Duquesne University of Pennsylvania does not have a predicted graduation rate, yet their Fall 1991 SAT scores [1000] are reported in the 1992 rankings and their FY1992 expenditures ($7,749) are reported in the 1993 rankings.) Such missing data can pose a problem in any analysis, with the result that institutions with missing data on one or more variables must be thrown out of the analysis. (An alternative approach is to impute the missing values based on the remainder of the sample. King et al., [1998] show the deleterious impact of case deletion due to missing values and offer a simple method for imputing missing values.) As more variables are added to the model, the probability of having missing data for a variable increases. In the National Graduation Rate Study, seventy-five institutions were solicited for data. Only fifty-two institutions responded with usable data files, and of these fifty-two institutions eight were removed from the analysis due to missing data for some variables.14

A more serious problem is the definition of the sample. USN relies on the higher education classifications developed by the Carnegie Foundation. Its classifications are based on the number of graduate degrees awarded, number of disciplines offered, and federal support awarded. While such classification systems may be laudable, they depend on somewhat arbitrary cutoffs for the measures of interest. Slight changes in cutoffs will change the makeup of the sample and, if the cutoffs are held constant, institutions will drift in and out of the sample over time as their programs and federal support change. Other sample definitions are even more arbitrary. Asin simply uses baccalaureate-granting institutions that participated in a survey, as did Howard et al.15

A comparison of the national university samples from the 1992 and 1998 rankings, which list score and graduation data for the 1991 cohorts, is illustrative. Of the 204 national universities in the 1992 rankings, seven were dropped from the national university sample in 1998. Thirty-one
### Table 1: Models of six-year graduation rates, Fall 1991 cohorts

<table>
<thead>
<tr>
<th></th>
<th>Full sample</th>
<th>Reduced sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Intercept</td>
<td>-83.394**</td>
<td>-88.879**</td>
</tr>
<tr>
<td>SAT</td>
<td>0.105***</td>
<td>0.102**</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Logged spending I</td>
<td>3.556</td>
<td>3.792</td>
</tr>
<tr>
<td></td>
<td>(2.029)</td>
<td>(2.127)</td>
</tr>
<tr>
<td>Logged spending II</td>
<td>4.231*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.801)</td>
<td></td>
</tr>
<tr>
<td>Public institution</td>
<td></td>
<td>-0.035</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2.227)</td>
</tr>
<tr>
<td>Total enrollment</td>
<td></td>
<td>0.138*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.065)</td>
</tr>
<tr>
<td>Religious affiliation</td>
<td>2.135</td>
<td>4.165</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2.578)</td>
</tr>
<tr>
<td>% African-American</td>
<td></td>
<td>0.061</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.078)</td>
</tr>
<tr>
<td>% female</td>
<td></td>
<td>0.307**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.068)</td>
</tr>
<tr>
<td>% of undergraduates &gt; 25</td>
<td>-0.367**</td>
<td>-0.277**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.045)</td>
</tr>
<tr>
<td>Housing availability</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annual tuition and fees</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>F statistic</td>
<td>253.6</td>
<td>258.0</td>
</tr>
<tr>
<td>adjusted R²</td>
<td>0.72</td>
<td>0.72</td>
</tr>
<tr>
<td>SEE</td>
<td>9.8</td>
<td>9.8</td>
</tr>
<tr>
<td>N</td>
<td>198</td>
<td>198</td>
</tr>
</tbody>
</table>

Note: * p < .05, ** p < .01.

*Defined as actual graduation rate minus predicted.

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The impact of sample design was assessed in two ways. First, we simulated random sample selection to estimate the information in the national universe. Second, we examined the 25% and 10% quartiles of the data. These quartiles were selected because those in the bottom quartile of the data are less likely to have had actual changes in graduation rates that would cause their decrease.

The graduation rate is presented as the proportion of six-year graduates of each cohort of entering freshmen. The data were first regressed on year of entry cohort and then on year of entry for the student by the year of entry cohort. The resulting average spending on instruction, average expenditures on related educational activities, and the average SAT scores reported for the sample.

### Table 2: Changes in graduation rates

<table>
<thead>
<tr>
<th></th>
<th>21% and over</th>
<th>11% to 20%</th>
<th>1% to 10%</th>
<th>0%</th>
<th>-1% to -10%</th>
<th>-11% to -20%</th>
<th>-21% and under</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.5</td>
<td>12.6</td>
<td>38.4</td>
<td>4.0</td>
<td>32.3</td>
<td>9.6</td>
<td>2.5</td>
</tr>
<tr>
<td></td>
<td>0.5</td>
<td>13.6</td>
<td>38.4</td>
<td>4.5</td>
<td>30.8</td>
<td>9.6</td>
<td>2.5</td>
</tr>
<tr>
<td></td>
<td>0.6</td>
<td>12.3</td>
<td>39.1</td>
<td>3.9</td>
<td>30.7</td>
<td>10.6</td>
<td>2.8</td>
</tr>
<tr>
<td></td>
<td></td>
<td>5.0</td>
<td>39.7</td>
<td>7.3</td>
<td>40.8</td>
<td>5.6</td>
<td>0.6</td>
</tr>
<tr>
<td></td>
<td></td>
<td>7.3</td>
<td>36.9</td>
<td>9.5</td>
<td>41.3</td>
<td>3.9</td>
<td>0.6</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>36.9</td>
<td>9.5</td>
<td>41.3</td>
<td>3.9</td>
<td>0.6</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
</tr>
</tbody>
</table>

Note: cell entries are the proportion.
universities not in the 1992 sample were added to the 1998 sample, resulting in a total of 228 national universities in 1998.

The impact of missing data and changes in sample definition can be simulated in two ways. First, institutions can be randomly removed from the sample to estimate the impact of potential missing data. Second, institutions from the bottom quartile of the rankings can be removed to simulate reclassification of institutions as national universities. Institutions in the bottom quartile of the rankings are chosen because those in the top three quartiles are less likely to experience such extreme changes in major and degree programs as to cause their reclassification.

The graduation equation used by USN is presented in column 1 of Table 1. The six-year graduation rate for the 1991 new freshman cohort in 198 institutions is regressed on the average SAT score for the cohort and the average expenditures per student by the institution, defined as the average spending per FTE student on instruction, research, student services, and related educational expenditures. The SAT scores reported by USN are actually averages and midpoints if the institution only reported 25th and 75th percentile scores. ACT scores were converted to SAT scores using a College Board concordance table. Ten institutions were randomly removed from both the entire sample and the bottom quartile and the graduation equation re-estimated. This process was then repeated an additional four times to estimate the graduation equation on ten different samples. The results are presented in Table 2, which shows the distribution of the change in predicted graduation rate from the full sample model for each of the trials for both simulations.

<table>
<thead>
<tr>
<th>Trial</th>
</tr>
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<tbody>
<tr>
<td>1</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td>4</td>
</tr>
<tr>
<td>5</td>
</tr>
</tbody>
</table>

Simply removing ten random institutions causes the predicted graduation rates to fluctuate plus or minus one percentage point. The changes occur on a sizable portion of the sample: in some trials fully 15-20 percent of the institutions changed predicted graduation rates. The sample change simulation produced similar results. Randomly removing ten institutions from the group in the bottom quartile of the rankings also causes the rates to fluctuate plus or minus one percentage point (and in one

Table 2: Change in predicted graduation rates due to changes in sample

<table>
<thead>
<tr>
<th>Change in predicted graduation rate from full sample model</th>
<th>Trial</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>5</td>
</tr>
<tr>
<td>Missing data simulation</td>
<td>-1</td>
</tr>
<tr>
<td>(10 institutions randomly removed from full sample)</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>5</td>
</tr>
<tr>
<td>Sample change simulation</td>
<td>-2</td>
</tr>
<tr>
<td>(10 institutions randomly removed from bottom quartile of sample)</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>5</td>
</tr>
</tbody>
</table>

Note: cell entries are numbers of institutions.
trial, two percentage points). Moreover, the number of institutions affected by the change is much larger, affecting around 25-50 percent of the sample.

From the results we can conclude that both missing data and different sample definitions will affect the predicted graduation rates from these models, even though the amount of change may not seem remarkable. But two points should be kept in mind. First, as researchers it is easy to dismiss such small changes as insignificant. But from the perspective of an individual institution, every percentage point counts: a two-point drop in its predicted graduation rate may seem very large indeed. Second, and more importantly, the simulations reveal that the data used cannot be considered the population of national universities; instead, the data must be viewed as a sample of all national universities. This distinction has a very important implication as to how we treat the predicted rates and will be discussed below.

**Variable Definition**

In addition to sample definition, there are several ways to define the explanatory variables in the graduation rate model. Should the quality of the cohort be expressed as the mean or the median SAT score? Either method is justifiable, yet it is likely that the two methods would yield different predicted graduation rates. Unfortunately the data are not available to test this possibility.

The expenditure data, however, is available for testing. In the latest rankings USN uses the average spending per FTE student on instruction, research, student services, and related educational expenditures as its measure of financial resources available to the institution.\(^{17}\) This variable is averaged over FY 1992-95 (the only years for which IPEDS data are available for the 1991 cohort) and is used as the expenditure variable in the model listed in column 1 of Table 1. In the 1992 rankings USN used a slightly different measure of financial resources: not only the sum of educational expenditures but also all other spending, including such areas as research, scholarships, and operations.\(^{18}\) The graduation model using this second formulation is shown in column 2 of Table 1.

The equations are quite similar: the coefficients change slightly, and the predictive ability of the equations as measured by the adjusted R-square and the standard error of the regression is the same. The one difference is that the spending variable in the second model is now significant at the .05 level. But since the error levels are similar for both variables (\(p = .08\) and \(p = .02\)), this difference is not as great as it might seem. The bottom portion of Table 1 shows the distribution of the difference between an individual institution’s actual and predicted graduation rates. Again, the two models seem very much alike. The results would appear to meet expectations about the impact of slightly changing the definition of an explanatory variable: the two measures of spending are highly correlated (\(r = .97\)) and thus the statistical results are similar.

Yet the predicted graduation rates do differ. Table 3 shows the changes in predicted graduation rates when the total expenditures spending variable from the second model is used instead of the reduced spending variable in the first model. The predicted graduation rates for over half the sample change, and for seven institutions the rate changes by at least minus two percent.

The results in Table 3 suggest a problem with the model definition. Seemingly irrelevant changes in the definition may have major effects on statistical results, raising the question of changes in the predicted graduation rates when all spending changes are either made or not made.

**Model Specification**

More serious than the model specification problem with the graduation rate model is the econometric model specification. The specification is specified when it is estimated. Thus, the underlying problem with model specification can be traced back to whether a model is completely or at all specified. Yet important is the case where a variable has been dropped from the equation, can yield the model specification.

<table>
<thead>
<tr>
<th>Change in predicted graduation rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>using total expenditures spending variable</td>
</tr>
<tr>
<td>-2</td>
</tr>
<tr>
<td>-1</td>
</tr>
<tr>
<td>0</td>
</tr>
<tr>
<td>+1</td>
</tr>
<tr>
<td>+2</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 3: Change in predicted graduation rate due to different spending</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change in predicted graduation rate using total expenditures variable</td>
</tr>
<tr>
<td>-2</td>
</tr>
<tr>
<td>-1</td>
</tr>
<tr>
<td>0</td>
</tr>
<tr>
<td>+1</td>
</tr>
<tr>
<td>+2</td>
</tr>
</tbody>
</table>
institutions the rates changes by plus or minus two percentage points.

The results in Table 3 point to another problem with studies of this type. Seemingly irrelevant changes in variable definition may have little impact on the statistical results, yet still cause substantial changes in the predicted values of the dependent variable. Careful thought must be given to how variables are defined before one can reach the conclusion that individual institutions are overperforming or underperforming.

### Model Specification

More serious than sample selection or variable definition is the specification of the graduation performance model. An econometric model is said to be correctly specified when it describes or represents the underlying process of interest. Model specification can be a dicey business since reasonable researchers can often differ as to whether a model has been correctly specified. Yet improper specification, as in the case where a theoretically relevant variable has been excluded from the equation, can yield biased coefficients in a regression model. And since the
coefficients are used to calculate a predicted graduation rate for individual institutions, poor model specification is not something that can be ignored.

With the graduation rate model we can attempt to assess model specification by asking two simple questions. Given that the model tries to measure student inputs to an institution as well as the constraints faced by an institution, does the model fully capture all of the relevant characteristics of the inputs, that is, the incoming student cohort? And does the model capture all, or even most, of the relevant constraints faced by an individual institution?

In the case of the USN model the answers are clearly no. Certainly other aspects of the incoming student cohort besides their SAT/ACT scores will affect their six-year graduation rate. And universities face other constraints on their behavior besides the amount of money they are able to spend. The remainder of this section describes other available variables that theoretically could be included in the model and assesses the impact of their inclusion on the predicted graduation rates.

### Additional Measures of Inputs and Constraints

Average SAT/ACT scores are included in the graduation models to measure an institution's "input"; Harvard attracts much more talented students than the University of Maryland, and this difference should be taken into account before either institution is judged on how well it graduates its students. But focusing only on standardized tests forces us to narrowly define academic credentials while also ignoring other aspects of the incoming student body. I consider three:
the proportion of minorities in the cohort, the proportion of females, and the proportion of the student body over 25 years of age.

To a certain extent academic credentials will be reflected in standardized scores, but standardized scores cannot capture all aspects of how well a child has been educated. Having access to college preparatory courses, for example, will affect how many credits a student brings to college and how soon they will graduate. In addition, family income will also affect the ability of students to stay in school and graduate. Given that some institutions recruit more students from disadvantaged backgrounds than others, this must be taken into account when assessing performance.

Unfortunately such data are difficult to find at the institutional level. As a proxy for the academic and financial background of the cohort 1 use the proportion of the Fall 1991 cohort that is African-American. Access to primary education in the USA is not equal across racial groups, and income disparities between blacks and whites are well known. Including this variable in the model helps take into account the fact that institutions recruit very different student bodies.

Differences in academic performance between males and females are also well known. Many universities are currently experiencing trouble recruiting male students, and some institutions do a better job of recruiting male students than others. Just as an institution should not be penalized for failing to recruit students with perfect SAT scores, they should also not be penalized because their incoming student cohort is not evenly split between genders. I control for this by including the proportion of the incoming cohort that is female. Race/ethnicity and gender are standard control variables in models of retention and should be in any model of graduation rates. Both the gender and ethnicity variables come from the IPEDS datasets.

Finally, the average age of the incoming cohort is included in the expanded model. Urban commuter schools, for example, tend to serve older student populations. Older students face a far different series of challenges than students fresh out of high school, such as financing issues and family responsibilities. Unfortunately the average age of the cohort is not collected by IPEDS or any other data source that I could find. As a proxy I include the proportion of the undergraduate student body over 25 years of age in Fall 1991 taken from Peterson's College Guide. The average age of the new student cohort should be highly correlated with the average age of the undergraduate student body, and any bias resulting from differences between the two should be more than offset by the reduction in bias by including a relevant independent variable.

I now consider additional ways of measuring constraints. Certainly the amount of money an institution is able to spend on its students is an important constraint on its ability to graduate them in a timely manner. But institutions just as certainly face other constraints that affect their ability to graduate students that should also be taken into account. I briefly discuss three such possible constraints: whether an institution is public or private, the total enrollment of the institution, and whether the institution has a religious affiliation.

Public institutions face a far different set of constraints than private institutions. They are usually more constrained by state agencies overseeing the quality of the institution than by the market. They can set tuition levels to match the capital improvements in faculty workloads, and buy out their employees. Public institutions also have more freedom to set policies that affect student success. Private freedom should be available in these models.

Total undergraduate body enrollment is a constraint that can affect both the graduation rate and the potential of public universities to fulfill the state's goal of reducing enrollments. Even if the school were not in financial difficulty, state legislators might use this constraint to support a centralization policy. Total enrollment can be easily disguised by creating new programs or by hiring visiting professors, but the undergraduate body enrollment cannot be viewed at a policy level as anything other than a constraint on the state legislature's ability to fulfill its goals.

While students graduating from the public system are supposed to spend their first 4 years at the university, little data exist on how the students' time is spent. Smaller institutions with larger enrollment ratios, with smaller student-faculty ratios, and students who are more likely to attend the community college in their early years, as suggested by the literature, 23 it is reasonable to expect that students might find it difficult to graduate on time. Even though the public institutions have a larger enrollment, their graduation rates are lower.

Large state universities may work in concert with the state government to increase returns to scale and to reduce the cost of enrollments in the in-state market.
Student stability and gender variables in models were included in any model of the gender and recipient from the IPEDS database. The growth of the incoming class of new or expanded schools, for instance, student attrition rates face a far more serious challenges than students face at more established schools. The average of the average, collected by the average of the institution, I include the net increase in student population. Guide. The graduate student cohort is used to average the average of the graduate student population. The growth from the growth in student enrollment in bias and concurrent dependent variables.

One major way of assessing the ability of an institution is the ability of the institution to graduate their students. The results from the growth in the student body size and the constraints that the institution places on the student body size. The student body size and the constraints that are placed on the student body size. The student body size is a major factor in the ability of the student body size to be integrated into the student body size.

While student body size may affect graduation rates, the direction is not clear. Smaller institutions are generally equated with smaller class size and more student-faculty interactions. Given the emphasis on integration within the university community in most of the retention literature, it seems likely that students would find it easier to become integrated in a university with a small undergraduate enrollment, thus increasing graduation rates. Large student enrollments, however, may work in the opposite direction due to returns to scale. With larger student enrollments it becomes cheaper to provide expensive infrastructure such as research laboratories, recreation facilities, or intensive student advising. Such infrastructure should also positively affect student behavior and thus graduation rates.

Finally, an institution's religious affiliation may also affect graduation rates. Universities with a religious affiliation are likely to provide a different atmosphere for their students than most institutions, as well as recruit different student bodies. Religious affiliations are usually historical in nature and cannot be considered something which universities can change as they please: in other words, a constraint.

In the expanded graduation model I include two dummy variables indicating whether an institution is public or has a religious affiliation, as well as the total undergraduate enrollment in Fall 1991. All data are from the IPEDS datasets.

Results

One problem associated with the inclusion of additional explanatory variables is missing data. For example, Peterson's did not report age data for several institutions. Nineteen institutions were thus dropped from the analysis due to missing data. The base graduation model was re-estimated for these institutions and the results presented in column 3 of Table 1. The estimates for the expanded model are presented in column 4. Several differences between the two equations are noteworthy.

First, the impact of SAT and spending on graduation rates change: the impact of SAT scores is reduced while the impact of spending increases. Second, three of the six additional variables are significantly related to graduation rates. All else being equal, institutions with large undergraduate
enrollments, large proportions of females, and younger students had higher graduation rates. Third, the expanded model does a better job of predicting graduation rates. The standard error of the regression or SEE is an estimate of the standard deviation of the forecast errors and is a vastly superior measure of model fit compared to the $R^2$. In other words, the base model can on average predict graduation rates plus or minus 9.9 percentage points, but the expanded model’s predictions fall within a smaller band, plus or minus 7.8 percentage points. This can be seen in the spread of the difference between actual and predicted graduation rates at the bottom of Table 1. Over 26 percent of the institutions in the reduced sample have predicted graduation rates 10 percentage points greater or less than their actual graduation rates. Using a more properly specified model this proportion drops to slightly more than 12 percent.

All of these differences illustrate how serious model specification is when attempting to predict graduation rates. Additional explanatory variables did not change hypotheses concerning the impact of SAT scores on graduation rates: SAT scores have a significant impact in both models. But the additional variables did affect the predicted graduation rates: the proportion of institutions with extreme performance differences dropped.

This point becomes clear when the data are presented in a different manner. Table 4 classifies the 179 institutions by whether they were underperformers (their predicted rates were higher than their actual rates), overperformers (their predicted rates were lower than their actual rates). If model specification made little difference in the predicted rates, we would expect to see all of the institutions fall in the bolded cells in a diagonal line. This is clearly not the case. By adopting a more complex view of the inputs and constraints faced by a university, we can cause thirty institutions to suddenly change from underperformers to overperformers. The changes here are not the result of changes in performance, but in the constraints (in this example, a reduction of one point).

Unfortunately, Table 4 is one of the thorniest for the analysis. While we agree with the statistics in column 4 of Table 2, we do not agree with the statistics in Table 4. Two independent variables were added: housing and production. Undergraduates are divided by the number of housing units and fees (both times enrollment, and by semester). Both were considered as inputs to the university.

Table 4: Changes in overperformance and underperformance, base and expanded models

<table>
<thead>
<tr>
<th>Performance</th>
<th>Under</th>
<th>No change</th>
<th>Over</th>
<th>TOTAL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Under</td>
<td>63</td>
<td>3</td>
<td>13</td>
<td>79</td>
</tr>
<tr>
<td>35.2%</td>
<td>1.7%</td>
<td>7.3%</td>
<td></td>
<td>44.1%</td>
</tr>
<tr>
<td>No change</td>
<td>4</td>
<td>1</td>
<td>2</td>
<td>7</td>
</tr>
<tr>
<td>2.2%</td>
<td>0.6%</td>
<td>1.1%</td>
<td></td>
<td>3.9%</td>
</tr>
<tr>
<td>Over</td>
<td>17</td>
<td>9</td>
<td>67</td>
<td>93</td>
</tr>
<tr>
<td>9.5%</td>
<td>5.0%</td>
<td>37.4%</td>
<td></td>
<td>52.0%</td>
</tr>
<tr>
<td>TOTAL</td>
<td>84</td>
<td>13</td>
<td>82</td>
<td>179</td>
</tr>
<tr>
<td>46.9%</td>
<td>7.3%</td>
<td>45.8%</td>
<td></td>
<td>100%</td>
</tr>
</tbody>
</table>

Note: institutions classified using predicted rates from equations in columns 3 and 4 of Table 1. Under is actual < predicted, no change is actual = predicted, and over is actual > predicted.
to overperformers, or vice versa (the changes here are not simply institutions moving from +1 to -1 in terms of performance; many of the institutions experienced swings of over 10 percentage points).

Unfortunately, model specification is one of the thorniest issues in econometric analysis. While most researchers might agree with the specification of the model in column 4 of Table 1, they might not agree with the specification in column 5. Two independent variables have been added: housing available to undergraduates, measured as the ratio of housing units available to undergraduates divided by the total undergraduate enrollment, and annual in-state tuition and fees (both as of the Fall 1991 semester). Both variables can be considered as programs and policies set by the university. If housing is in demand, the university can simply build more housing. And if tuition is too high or low, the university is free to change it as well. In this view these variables should be included in the model as constraints.

The SEE reveals that this model does an even better job of predicting graduation rates, and the distribution of over/underperformance compared to the results in column 4 indicates that the predicted graduation rates fluctuate. Which model should be used? If both models can be justified on theoretical grounds, how reliable are the predicted graduation rates if they change with simple changes in model specification? This illustrates one of the major problems with research in this area. If simple changes in model specification can cause changes in predicted graduation rates, it becomes difficult to defend the practice of listing institutions by their supposed graduation performance. How well an institution does depends not only on their programs and policies; performance also depends on the whims of the researcher.

Confidence Intervals
This section considers the fourth criticism of the graduation rate models: the treatment of the predicted values from the regression equation. When estimating a regression model researchers report confidence intervals for the coefficients for each independent variable, usually in the form of standard errors or t-statistics. They do so because the data analyzed are usually from a sample of a larger population. Because of sampling variation we cannot be certain that the relationships found within the sample mirror those in the population, and confidence intervals allow us to assess the probability that the relationships in the sample (under repeated sampling) would also be found in the population.

If the data used in the analysis consist of a population, then confidence intervals are unnecessary, because there is no possibility that the relationships found do not exist in the population. Researchers in the graduation rate performance area implicitly use this assumption when reporting predicted graduation rates without confidence intervals. Unfortunately this assumption is unwarranted for two reasons.
First, we can never be certain that we have obtained data for the population of national universities. Consider the Carnegie classifications. If cutoffs based on number of programs and research dollars are used to define the population, how can we be sure we are not excluding universities that might be considered “national” from a theoretical point of view? And if the cutoffs are only redefined every few years, in the years between reclassifications some institutions will become national according to the definition, but will not be included in the population until the next reclassification. If the data are collected by survey, the problem becomes even worse. If only one institution does not respond, then the data used for the analysis automatically becomes a sample. Examination of the Astin and Kroc et al., analyses reveals nonresponse to be a serious problem, as well as deletion of institutions due to missing data. Table 2 indicates how much the results can vary when missing data is a problem.

Second, suppose we are somehow able to obtain data for the population of national universities. Undoubtedly, mistakes have been made in the data collection process. For the data to reach its final form, programmers at individual institutions must run numerous computer programs; the data must be transcribed to the survey form; once collected, the surveys must be entered into a database for analysis. Errors can and will occur along every step, and if the process was repeated several times the resulting datasets would all differ in some small way. So even if data are obtained from a population of institutions, the data must be viewed as a sample of the “true” data and not the actual correct data themselves.

Understanding that the predicted graduation rates have a random component has serious implications for what we can say about institutional performance. Error is introduced into the predicted graduation rates in several ways. First, even if the estimated coefficients (or relationships between the independent variables and graduation rates) in the sample are exactly the same in the population, the random nature of the error term in the regression model ensures that the predicted values will differ from the true predicted values. Second, it is unlikely that the estimates of the coefficients will exactly equal those in the population, introducing further error. Third, if the model is misspecified and does not represent the “true” model of graduation rate performance the predicted values will contain additional error.

Such error must be taken into account when comparing predicted to actual graduation rates. The predicted rate may be higher or lower than the actual rate, not because of institutional performance but simply because of random error. The calculation of a confidence or prediction interval for an individual forecast has a similar interpretation as the standard error of the regression: the predicted value is expected to fall within plus or minus a certain number of percentage points. If the actual graduation rate falls within this bracket, then we must conclude that there is no statistically significant difference between the forecasted graduation rate and the actual graduation rate for an institution.

Prediction intervals were calculated for both the full sample using the base USN model in column 1 of Table 1, and the reduced sample using the expanded model in column 4 (see Table 5). Only 5 percent of the institutions have predicted graduation rates that lie outside their 95 percent prediction interval. For a rigorous 90 percent confidence interval, the percentage of institutions reporting the percentage of institutions reporting the percentage of institutions reporting the percentage of institutions reporting their predicted and actual graduation rates

| Table 5: Percent of institutions from their actual graduation rates

<table>
<thead>
<tr>
<th>Base model</th>
<th>Expanded model</th>
</tr>
</thead>
<tbody>
<tr>
<td>95%</td>
<td>90%</td>
</tr>
</tbody>
</table>

Using equation 1 and 2.
The Robustness of the Graduation Rate Performance Indicator

Implications for institutional policies in several ways. The predicted coefficients (or independent variables) in the regression model ensure that the predicted and actual rates will differ from each other. Second, it is possible that some institutions may have lower actual graduation rates than their predicted rates.

The "true" model of prediction has a residual error term, which is the difference between the predicted and actual values. The standard error of the predicted value is calculated as the square root of the mean squared error or minus a multiple of the standard error of the regression coefficient.

If a predicted value falls outside the range of the actual values, it can indicate that there is a significant difference between the predicted and actual values. For an accurate forecast, the predicted value should fall within the range of the actual values.

The table below shows the percentage of institutions whose predicted graduation rates significantly differ from their actual graduation rates.

<table>
<thead>
<tr>
<th>Model</th>
<th>Using 95% confidence interval</th>
<th>Using 90% confidence interval</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>%</td>
</tr>
<tr>
<td>Base model</td>
<td>9</td>
<td>4.5%</td>
</tr>
<tr>
<td>Expanded model</td>
<td>9</td>
<td>5.0%</td>
</tr>
</tbody>
</table>

Table 5: Percentage of institutions whose predicted graduation rates significantly differ from their actual graduation rates

footnotes:

1. Using equation in column 1 of Table 1.
2. Using equation in column 4 of Table 1.

Conclusion

The data presented here raise serious questions about the graduation performance enterprise embarked upon by many analysts. While attempts to hold institutions accountable and assess their performance are laudable, research in this area must be above reproach. The results of these models are taken seriously by institutions and can have quite an impact in the real world. (See Mufson 1999 for a description of how George Washington University's business school spent $1.5m and radically restructured its program solely to improve its position in USN's rankings. But Hollander and Foley [1995] argue that the rankings have little impact on student choice.)

While...
publication of simple graduation rates has been charged as misleading,29 the results indicate that “value-added” models that attempt to take into account an institution’s inputs are as much, if not more, misleading.

This analysis demonstrates that the models used to assess graduation rate performance are highly sensitive to sample and variable definition and model specification. Given how predicted graduation rates fluctuate depending on what model is used and how its variables are defined, it becomes impossible to defend conclusions such as, “apparently Alaska institutions do not provide academically supportive environments leading to graduation within six years [because their actual rates are less than their predicted rates]”.20 Worse, proper statistical use of the predicted graduation rates reveals that research in this area is very much a case of the emperor’s new clothes: 95 percent of the institutions in this study have predicted graduation rates that do not significantly differ from their actual graduation rates.

The results presented here can be viewed as a doubled-edged sword. While institutions are quick to laud the USN rankings when their particular institution does well, a drop in rank causes severe problems: “drops need to be explained to alumni, trustees, parents, incoming students, and the local press”.31 To the extent such negative changes can be explained by methodological causes, analyses such as this one can be very valuable in defending an institution from criticism it is not doing enough to maintain quality.

Yet as Machung has so astutely noted,32 USN actually encourages complaints about the construction of their rankings. By incorporating criticisms of their methodology in next year’s rankings, USN guarantees a substantial amount of movement in the rankings, movement that would most likely not occur without such changes. These fluctuations generate substantial publicity for their rankings, for example most recently when Caltech was declared the “best” college in the country. And increased publicity, of course, leads to increased sales. So taking into account methodological critiques such as those presented here may actually increase fluctuations in the rankings.

Unfortunately advancement staffs are placed in a difficult position. They can explain drops in rank to internal and external constituencies by criticizing the particular methodology used. When such critiques are taken into account, their institution may jump in rank one year. But advancement personnel at other institutions are also pressuring USN to change its methodology to their benefit, resulting in yet another drop somewhere down the line. The result is a somewhat vicious circle, with institutions first clamoring for changes and then dealing with the fallout, which in turn initiates another round of complaints about USN’s methodology, and another set of fluctuations in the rankings.

Appendix – Data Description and Sources
The USN dataset consists of 218 of the 228 institutions in its national university sample (ten institutions are listed as ‘N/A’ for their predicted graduation rate—I assume these institutions were excluded from the data it analyzed). The data analyzed in this paper contain only 198 institutions.

Table A-1: 6-Year Graduation Rate

<table>
<thead>
<tr>
<th>Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted graduation rate</td>
</tr>
</tbody>
</table>

29Taken from Source
30Based on equation

Table A-2: Institution Data

<table>
<thead>
<tr>
<th>Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fiscal year</td>
</tr>
<tr>
<td>SAT/ACT scores</td>
</tr>
<tr>
<td>Gender</td>
</tr>
<tr>
<td>Student body</td>
</tr>
<tr>
<td>Institution type</td>
</tr>
<tr>
<td>Religious affiliation</td>
</tr>
<tr>
<td>% of undergrads</td>
</tr>
<tr>
<td>Annual in-state tuition</td>
</tr>
<tr>
<td>Number of bachelor degrees</td>
</tr>
</tbody>
</table>

Two of the highest USN university rankings in the 1992 publication of The University of Alabama were excluded from this analysis. In addition, SAT/ACT scores were not available for these institutions as well as some later years’ rankings. After removing several schools, leaving 218 institutions for analysis.

Table A-1 shows the predicted graduation rates for each institution in the samples. The Predicted graduation rate reflects the model estimates of the rates.
Incorporating criticisms in next year’s survey is impractical given the substantial publicity generated by the USN. Other schools would most likely not be interested in being a part of such an exchange. These schools, which are not mentioned in national surveys but which were declared the best in the country, avoid the publicity by being unranked. This, of course, leads to rankings that are not as meaningful as those taking into account the average quality of all the institutions in the country. And so the USN rankings, which are based on influence, lead to rankings that are not as meaningful as those taking into account the influence of all the institutions.

The rankings of academic staffs are not supported by the quality of their academic programs. They can be improved by reducing student/teacher ratios or by increasing the size of the student body. This, of course, has to be done with the consent of the students. The USN rankings are based on student/teacher ratios and then dealing with student/teacher ratios. The USN rankings are based on student/teacher ratios and then dealing with student/teacher ratios. The USN rankings are based on student/teacher ratios and then dealing with student/teacher ratios.

Table A-2: Data sources

<table>
<thead>
<tr>
<th>Variable</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Six-year graduation rate</td>
<td>Smith (ed.) (1998), America’s Best Colleges</td>
</tr>
<tr>
<td>SAT/ACT scores</td>
<td>L. Dilts (ed.) (1990)13 or the institution</td>
</tr>
<tr>
<td>Fiscal year expenditures</td>
<td>IPEDS</td>
</tr>
<tr>
<td>Gender and minority data</td>
<td>IPEDS</td>
</tr>
<tr>
<td>Student body totals</td>
<td>IPEDS</td>
</tr>
<tr>
<td>Institution type</td>
<td>IPEDS</td>
</tr>
<tr>
<td>Religious affiliation</td>
<td>IPEDS</td>
</tr>
<tr>
<td>% of undergraduates 25 and over</td>
<td>Elfin and Brophy (1992)24</td>
</tr>
<tr>
<td>Annual in-state tuition and fees</td>
<td>Elfin and Brophy (1992)</td>
</tr>
<tr>
<td>Number of housing spaces for undergraduates</td>
<td>Elfin and Brophy (1992)</td>
</tr>
</tbody>
</table>

Two of the 218 institutions, the University of Memphis and the University of Alabama at Tuscaloosa, do not appear in the 1992 IPEDS enrollment data and were excluded from the analysis. In addition, SAT/ACT data for many institutions were not listed in the 1992 rankings. After querying the institutions I was able to fill in the data for some schools, leaving 198 out of the original 218 institutions in my dataset.

Table A-1 lists some information on the predicted graduation rates for both samples. The predicted graduation rate statistics reported for USN are calculated on the rates published in the latest rankings. Following USN, predicted values greater than 100 were reset to 100. Despite the lack of an exact match between the two datasets, they do appear quite similar.

Sources for the data used in the analysis are given in Table A-2.

References


7. Ibid., emphasis added.


12. See Smith (ed.) (1998), America's Best Colleges, p. 37 for details about their sample; see the Appendix for a description of the differences between the two datasets and data sources.


27. Ibid., pp. 206–11.


Practitioners’ Perspectives

The proliferation of surveys and polls conducted by national media that rank colleges and universities has created concern on campuses nationwide. While most academicians question the methodology of these efforts, advancement professionals, as laypeople, are left the task of explaining these rankings to our respective alumni, faculty, staff, students, and friends. Of particular concern in recent years has been the reporting of graduation rate performance indicators. These rankings are often distorted, and they do not represent a true measure of actual or predicted graduation rates.

Steve Porter discusses this practice in his paper “The Robustness of the Graduation Rate Performance Indicator Used in the U.S. News & World Report College Rankings.” He contends that graduation rates as a measure of success or productivity of a college or university must be used with caution. Although graduation rates are used to some degree as a measure of accountability by most states, the methodology to determine actual and predicted graduation rates varies widely. The result is that there is no nationally agreed upon methodology for measuring graduation rates among institutions. In fact, there are no national standards for gathering data for any of the most commonly agreed upon measures of accountability.

The State Higher Education Executive Officers (1991) published a report titled Assessing and Reporting Student Progress: A Response to the “New Accountability.” Included in the report are recommendations for a basic reporting system to track student progress at institutions of higher education. Proposed standard reporting statistics discussed in the report include the percentage of students completing programs, average time to degree completion, percentage of required credits completed at graduation, and degree earned.

The American Association of State Colleges and Universities (1995) addressed the issue of accountability reporting in its annual Report of the States. Although there is no consensus among states or among institutions regarding what accountability measures should be, there has been some movement toward agreement of what performance indicators for state colleges and universities might be.

Porter does an excellent job of demonstrating the effect of using different measures for accessing predicted graduation rates. He explains the USN performance
indicator, which is calculated as the difference between an institution's actual graduation rate and its predicted graduation rate from a linear regression equation controlling for student aptitude and institutional expenditures. The sample is 198 of 218 national universities used in USN's 1999 rankings. However, he also demonstrates how changes in sample and variable definitions greatly affect the predicted graduation rates for an institution. The implication is that USN's methodology is flawed and perhaps should be abandoned, and at the very least approached with caution.

While it is unlikely that national publication of questionable data concerning institutions of higher education will cease, at least it is being called into question. Porter's research ultimately gives advancement professionals some quantitative information to explain to constituents why surveys and polls, like USN's, often provide misleading information and should not be used by themselves to judge a particular institution.

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