A New Approach to University Rankings Using Latent Variable Analysis

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Abstract

This study applies a Bayesian latent variable analysis to the task of determining rankings of universities in the U.K. and U.S. on the basis of a set of quality-related measures. It estimates the degree of uncertainty in the rankings and permits the assessment of statistically significant differences across universities. It also provides a methodology for determining the weighting of various measures that is based on the patterns embedded in the data and compares the latent variable rankings with traditional weight-and-sum rankings. Overall, the methodology contributes to a better understanding of ranking efforts and illustrates the need for caution in interpreting distinctions published in traditional ranking systems.

Introduction

Interest in rankings of institutions of higher education has intensified over the course of the last two decades. Ranking efforts have expanded considerably since the publication of the first *U.S. News & World Report* (*USNWR*) annual ranking of "America's Best Colleges" in 1983. In addition to several popular ranking systems in the United States[1] and the United Kingdom,[2] many others exist in other countries.[3] Since 2003, two ranking systems that span international borders have emerged—the "Academic Ranking of World Universities" published by the Shanghai Jiao Tong University and the "World University Rankings" published by *The Times Higher Education Supplement.* The trend suggests that these systems will continue to proliferate.

Most ranking systems use a "weight-and-sum" approach. They collect university-level data on a set of measures considered to be related to educational quality, such as the selectivity of the student body or ratings of prestige. They then assign weights to each measure, generally based on subjective opinions of the relative importance of each indicator, and sum the weighted measures for each institution. The weighted sums produce an ordinal ranking of institutions. These rankings, however, can be somewhat misleading in that they may "over-differentiate" among institutions, assigning different rankings to institutions that may be more or less indistinguishable.

This paper proposes an alternate approach to ranking institutions along observable quality-related dimensions. The approach involves the use of a statistical procedure known as latent variable analysis. The result is a sequential ordering of individual institutions that carries with it information that allows us to assess whether differently ranked institutions are statistically distinguishable.

Our proposed approach can be used to address a number of issues related to university ranking systems. In this study, we answer the following questions:

1. How do we properly account for uncertainty in the assignment of ranks to different institutions?
2. When are measured quality differences between institutions statistically significant?

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[1] See *U.S. News & World Report*'s "America's Best Colleges," *Barron's Profiles of American Colleges*, *The Top American Research Universities*, published by The Center at the University of Florida, and Avery et al. (2004).

[2] See *The Times Good University Guide*, the *Guardian University Guide*, and the *Sunday Times University Guide*.

[3] See, for example, *Maclean's Guide to Canadian Universities* and Hobson's *Good Universities Guide* and the *Melbourne Institute Index of the International Standing of Australian Universities* for Australia.

3. How important are different input measures to the overall ranking?

Answers to these questions have practical implications for potential students and the higher educational institutions themselves. Answers to the first two questions allow us to obtain a sense of the degree to which certain institutions are similar or dissimilar as well as allow the possibility of differentiating among institutions in a meaningful way. An answer to the third question can reveal the nature of the factors creating similarity or dissimilarity.

The proposed latent variable approach is not a panacea, however. Like weight-and-sum ranking systems, the approach relies on observable "quality" indicators and does not offset the deficiencies inherent in the indicators themselves or in the manner in which they are operationalized and measured. Better measures of what students gain from attending an institution would improve the precision of current ranking methods as well as the approach proposed here. Lacking better data, however, we illustrate the latent variable method with existing data from two prominent ranking systems, *The Times Good University Guide* and the *USNWR*, and discuss important advantages of this approach over the standard weight-and-sum approach.

Background

Ostensibly, rankings serve an important purpose in providing information to the general public and a means of fostering accountability. Shattock (2003, p. 5) states, "There can be no doubt of the public interest in such assessments, nor that such interest has legitimacy, and any evaluation of university success must take their findings seriously." Rankings are closely followed by university administrators and affect policy choices. Monks and Ehrenberg (1999) found, for example, that the admissions and pricing policies of highly selective U.S. institutions of higher education were linked to the rankings published by the *USNWR*.

Existing ranking systems have been subject to a litany of criticisms. University administrators complain because they must struggle to deal with the consequences of shifts in annual rankings, and some[4] have questioned the integrity of the entire enterprise. At the most basic level, rankings have reframed higher education as a consumer good; doing so requires the savvy participant to think in terms of an abstract "best model" as well as the best value for the dollar, as emphasized in the *USNWR*. Recent studies lend validity to this notion. Brewer, Eide, and Ehrenberg (1999), Hoxby (2001), and Black, Daniel, and Smith (1997) find that the earnings of students from prestigious or highly ranked institutions are significantly higher than those of students with similar backgrounds who attend less prestigious colleges.

Setting aside the normative question of whether or not rankings *should* be done, rankings are handicapped at the outset by methodological concerns. First and foremost, no clear nor universally agreed-upon measure of quality in higher education exists.

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[4] http://news-service.stanford.edu/news/1997/april23/usnstatement.html, last retrieved April 12, 2005.

Absent any consensus, each ranking system combines an available set of observable indicators—each of which serves as a rough proxy for some factor notionally tied to quality—in a formula that can be questioned both on the basis of its contributing elements and the manner in which the elements are combined.

Second, when considering multiple ranking systems, it becomes questionable whether or not meaningful differences between institutions exist. A strong and noteworthy criticism of ranking systems is that statistically significant differences generally do not emerge between adjacently ranked universities or even between universities that find themselves at a distance from one another the rankings (Clarke, 2002a, 2002b).

Third, ranking systems are not neutral to the institutions they study but instead affect them. Many ranking systems heavily weight indicators of reputation, for example. Given that the rankings themselves play a prominent role in affecting reputation, the circular nature of these endeavors makes them a particularly strong self-perpetuating force. Thus, it is important to ask whether this force acts in the best interest of students and society. If universities are to be judged by the standards set by ranking systems and have strong incentives to conform to them, does moving in this direction take us closer to or further from true educational quality? And, if moving in this direction is inevitable, can we ensure that the rankings be carried out in a responsible manner?

Due to the potentially significant consequences these rankings have in influencing student choices and institutional behavior, the higher education community should encourage improved ranking methodologies and the collection of better measures of quality. In this paper, we describe a new methodological tool for examining quality differences among institutions and illustrate the efficacy of the tool using existing data measures. The new approach can supplement existing ranking methodologies and provide insights into the nature of distinctions among institutions.

Data

The data for this study are drawn from primary data used to construct rankings systems in the United Kingdom and the United States. The first dataset is from *The Times Good University Guide 2005,* and the second is from the *USNWR*.

The Times Good University Guide Data

The Times has been publishing institutional rankings since 1992. Nine indicators are used in the calculation of the rankings. They are based upon the data collected by the Higher Education Statistics Association to support the resource allocation decisions of the Higher Education Funding Councils. The indicators and their assigned weights are described in Table 1.[5] More detailed explanations regarding the indicators can be found in *The Times Good University Guide 2005.*[6]

Table 1. Indicators and Weights Used in The Times Good University Guide 2005

University feature	Weight	Description
Teaching	2.5	University-wide average of Teacher Quality Assessment scores in individual departments. Maximum possible score is 24.
Research	1.5	University-wide average of Research Assessment Exercise scores in individual departments.
Entry standards	1	Average A-level score (or Scottish Higher score) of new students under the age of 21. Maximum possible score is 30.
Student-to-staff ratio	1	Number of student full-time equivalents (FTE) divided by total teaching FTE.
Library and computer spending	1	Spending on library staff and holdings and computer hardware and software divided by student FTE.
Facilities spending	1	Spending on facilities divided by student FTE.
Percent high degrees	1	Percentage of graduates achieving first and upper second class degrees.
Graduate destinations	1	Proportion of graduates that enter further study or a graduate track job.
Completion rate	1	Length of time students take to complete degree compared with length of time they would be expected to study if they completed the course normally.

Source: *The Times Good University Guide 2005*.

Table 2 displays the means, standard deviations, and minimum and maximum values of the quality indicators pertaining to the 99 institutions of higher education represented in the dataset for the U.K. A quick inspection of this table suggests that some of these variables have a higher degree of variability than others. The facilities, library, and research variables, in particular, exhibit a wide range of values.[7] It is worth noting that all variables are significantly correlated with one another, and many of the correlations are high. Only the library, facilities, and destinations variables show correlations with other variables that fall below 0.5.

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[5] We obtained permission from *The Times* to use these data.

[6] In particular, see pages 13-18.

[7] This can be seen from both the range and the coefficients of variation—i.e., the standard deviation divided by the mean. For the facilities, library, and research variables, the coefficients of variation are equal to 0.41, 0.38, and 0.38, respectively.

Table 2. Descriptive Statistics for Features of Universities in the U.K.

University features	Number of universities	Mean	Standard deviation	Minimum	Maximum
Teaching	99	21.48	0.82	18.8	23.1
Research	99	4.01	1.52	0.5	6.6
Entry standards	99	18.68	4.84	11.5	29.5
Percent high degrees	99	59.52	10.53	39.3	89.3
Destinations	99	71.57	6.87	54.9	89.8
Completion rate	99	85.29	6.53	65	98
Faculty-student ratio	99	0.06	0.02	0.04	0.14
Library	99	565.61	215.15	321	1552
Facilities	99	196.07	79.46	11	460

Source: Statistics computed using data from *The Times Good Universities Guide 2005*.

U.S. News & World Report Data

The *U.S. News & World Report* (henceforth referred to as *USNWR*) builds a dataset for its annual publication of "America's Best Colleges."[8] The *USNWR* provides separate rankings for several categories of higher educational institutions: national research universities, liberal arts colleges, master's granting institutions, and comprehensive colleges. For the sake of brevity, we utilize only data related to national research universities in this study. In addition, although the *USNWR* provides data on 249 research universities, it ranks only the top 129 universities and reports fewer data for the others. Therefore, we restrict our analyses to these 129 institutions.

The *USNWR* rankings use seventeen measures considered related to institutional quality. These are shown in Table 3.[9] Only fourteen of these were available on the website. The *USNWR* uses a two-fold weighting scheme in which subfactors are combined with assigned weights to form aggregate factors and the aggregate factors are combined with assigned weights to form the total score.

[8] The data were obtained at http://www.usnews.com/usnews/home.htm, as of November 30, 2004. We obtained permission from the *USNWR* to use these data.

[9] More details can be found at http://www.usnews.com/usnews/edu/college/rankings/about/weight_brief.php#giving

Table 3. Indicators and Weights Used in the USNWR University Rankings

Aggregate Category	Category Weight	Subfactor	Description	Subfactor Weight
Peer assessment survey	25%		Survey of presidents, provosts, and deans of admissions in which schools are rated from 1 (lowest quality) to 5 (highest quality)	100%
Graduation and retention rate	20%	Actual 6-year graduation rate	Proportion of students entering between 1994 through 1997 who graduated within 6 years	80%
		Average freshman retention rate	Proportion of students entering in 1999-2000 who returned the following fall	20%
Faculty resources	20%	Proportion of small classes	Proportion of classes with fewer than 20 students	30%
		Proportion of large classes	Proportion of class with 50 or more students	10%
		Faculty compensation *	Average faculty pay plus benefits	35%
		Percent faculty with top terminal degree *	Percent of faculty with a Ph.D. or highest degree possible in their field	15%
		Student/faculty ratio	Ratio of student FTE to faculty FTE	5%
		Proportion full-time faculty	Proportion of 2003-2004 FTE faculty that was full-time.	5%
Student selectivity	15%	SAT/ACT scores	25th and 75th percentile of the university's distribution of Scholastic Aptitude Test (college entrance examination) scores of entering students	50%
		Proportion of top 10% students	Proportion of first-year students who graduated in the top 10 percent of their secondary school class	40%
		Acceptance rate	Ratio of students admitted to total applicants	10%
Financial resources #	10%		Average educational expenditures per student	100%
Graduation rate performance	5%		Difference between actual 6-year graduation rates and predicted rate based on the characteristics of the institution and entering students.	100%
Alumni giving rate	5%			100%
Total	100%			

Source: *USNWR's* "America's Best Colleges 2005."
* Measure not available.
# Expenditures per student was not available on the website but the university's rank on this measure was.

Table 4 shows descriptive statistics for these measures for the subset of 129 research universities. A considerable range in the indicators across schools is evident.[10] As was the case with the variables associated with U.K. universities, most of these variables are highly and significantly correlated.

Table 4. Descriptive Statistics for Features of 129 Research Universities in the U.S.

University features	Number of universities	Mean	Standard deviation	Minimum	Maximum
Peer assessment	129	3.5	0.6	2.5	4.9
Acceptance rate	129	0.57	0.22	0.10	0.93
Proportion of top 10% students	128	0.53	0.26	0.16	0.99
SAT score at 25th percentile	129	1136	116	840	1460
SAT score at 75th percentile	129	1335	104	1170	1590
Proportion full-time faculty	129	0.90	0.07	0.69	1.00
Faculty-student ratio	129	0.09	0.04	0.05	0.33
Proportion classes smaller than 20	129	0.48	0.14	0.19	0.75
Proportion classes smaller than 50	129	0.12	0.07	0.01	0.31
Average freshman retention rate	129	0.89	0.06	0.77	0.98
Actual 6-year graduation rate	129	0.74	0.12	0.48	0.98
Graduation rate performance	129	0.73	0.12	0.50	0.94
Financial resources rank	129	75.40	50.3	1.0	200.0
Alumni giving rate	129	0.21	0.10	0.05	0.61

Source: Statistics computed using data from the *USNWR*'s "America's Best Colleges 2005."

Methods

We used a statistical technique to estimate a university's "quality" based on a set of observable features. This technique is a Bayesian latent variable model. Bayesian methods have been used for ranking in other education-related studies. Lockwood, Louis, and McCaffrey (2002) discuss uncertainty in ranking teachers and schools from individual student test scores. Laird and Louis (1989) use an empirical Bayes approach to rank schools by their ability to affect student achievement. Goldstein and Spiegelhalter (1996) advocate Bayesian analysis for ranking individuals and institutions and use Markov Chain Monte Carlo integration to compute uncertainty in the ranks. These studies all involve ranking units on a single measure (e.g., teacher effects). In contrast, we rank universities simultaneously incorporating several measures. Our latent variable

[10] The coefficients of variation for the percentage of students in the top 10 percent of their class and for the alumni giving rate are higher than 0.60.

model essentially maps these measures to a single factor from which we can produce ranks.

The latent variable technique differs from standard weight-and-sum rankings because it (1) determines the relative importance of different university features using information embedded in the data rather than subjective opinion and (2) simultaneously determines the degree of uncertainty that surrounds the ranks. If an institution is clearly superior to all others on virtually all measured features, our method will find very little variance in its rank and will rank it as number one with a high degree of certainty. Alternatively, if an institution has features that weakly distinguish it from other institutions (e.g., its graduation rate is average), then there will be many similar institutions. Since we allow for variability in how influential particular features are on the measure of overall school quality, slight changes in the graduation rate's influence can permute the ordering of the schools near the middle. Analogously, in weight-and-sum approaches many universities end up being clustered in the middle, all with very similar overall scores. Slightly perturbing the weight for important variables can swing the rank of a university in this group by 20 or more universities. In such a situation our method would supply a ranking but the ranking would be accompanied by a great deal of uncertainty. Thus, it might be ranked, say 50^{th}, but it would not be possible for us to assert that it was statistically superior to the 51^{st} ranked university. In the next few paragraphs we provide a concise technical explanation of the methodology.

In the model, we suppose that each university has an unobserved, latent "quality" feature denoted z_i. While we do not observe each university's z_i directly, the university's observable features express the university's quality. More precisely, we use a linear model to associate the observed features, $x_1,\ldots,x_J$, with z_i. For the UK universities, for which we have nine measurements on each school, we will have a system of nine regression models of the form:

$$\begin{aligned}
\text{teaching}_i &= \beta_0^{(1)} + \beta_1^{(1)} z_i + \varepsilon_i^{(1)}, && \varepsilon_i^{(1)} \sim N(0,\sigma_1^2) \\
\text{research}_i &= \beta_0^{(2)} + \beta_1^{(2)} z_i + \varepsilon_i^{(2)}, && \varepsilon_i^{(2)} \sim N(0,\sigma_2^2) \\
&\vdots \\
\text{facilities}_i &= \beta_0^{(9)} + \beta_1^{(9)} z_i + \varepsilon_i^{(9)}, && \varepsilon_i^{(9)} \sim N(0,\sigma_9^2)
\end{aligned}$$

Note that there are nine different intercept terms, β_0s, nine different coefficients on z_i, the β_1s, and each regression model has its own residual variance. There is no need to shift and rescale the observed features since this is built into the model. This model is similar to a factor analysis with a single factor. We take a Bayesian approach, obtaining a posterior distribution for the latent z_is and compute the distribution of the university ranks.

Briefly, the Bayesian approach aims to compute the joint distribution of all the unknown quantities (the regression parameters and the z_is) conditional on the observed quantities (the university features). This posterior distribution captures all of the uncertainty about the unknown quantities. This framework is particularly helpful for ranking institutions. Not only will we be able to describe the uncertainty in estimating the z_is but also the uncertainty in their ranks relative to one another.

To complete the model specification, we put non-informative priors on the regression parameters and a Gaussian prior on the z_is with mean 0 and variance 1. Note that the location and scale of the z_is is not identifiable (nor of interest) since any shift in the z_is can be offset by a shift in β_0 and any rescaling of the z_is can be offset by scaling β_1.

While the complete joint posterior distribution of the z_is, βs, and σ^2s is complex, the posterior mean of z_i, given all the other parameters and observed data, is a simple linear combination of university i's observed features. The posterior mean of z_i given all other parameters is

$$E(z_i \mid \cdot) = a + b\sum_{j=1}^{J} \frac{\beta_1^{(j)}}{\sigma_j} \frac{x_j - \mu_j}{\sigma_j} \tag{1}$$

where a and b, respectively, shift and scale so that collectively the z_is have mean 0 and variance 1. Note that the absolute size of z_i is unimportant—only its position relative to other universities matters. The estimated mean of z_i is thus computed using a weight-and-sum method with each standardized feature j weighted with $w_j = \beta_1^{(j)}/\sigma_j$. Thus, as opposed to other weight-and-sum approaches that assign subjectively determined weights to the observable features, this method simultaneously estimates ranks and weights. We report estimates of the w_js, which inform us as to the relative contribution of the particular feature in determining the rank.

The z_is and the regression parameters are estimated jointly. The estimation algorithms iterate between computing the conditional distribution of the z_is and computing the conditional distribution of the regression parameters. If the z_is are known then the remaining parameters are easily estimable with standard linear regression. Both the EM algorithm and the Gibbs sampler operate in this fashion. We used a Gibbs sampler as implemented in OpenBUGS[11] to draw samples from the distribution of the z_is given the observed university features. With each draw from this distribution we obtain a set of z_is, and by ordering these z_is, we can derive ranks. This process is repeated many times. From 10,000 draws, we can get an accurate estimate of the distribution of the rank of the z_i for each university. For each university, we report the median rank as well as the ranks at the 2.5 and 97.5 percentiles computed over the 10,000 draws. The 2.5 and 97.5 percentiles bound a 95-percent posterior probability interval, similar to a confidence interval.

Findings

This section describes our analyses ranking universities in the U.K. and U.S. The analysis is structured in three steps for each country:

1. The latent variable measure is used to rank institutions and reveal the degree of uncertainty or variance associated with each ranking.
2. The results show the relative importance of different quality input measures for the overall latent variable ranking.
3. The new latent variable ranking is compared with existing rankings based on the same data measures.

[11] See mathstat.Helsinki.fi/openbugs/.

Results for Universities in the U.K.

Figure 1 displays the new rankings by university for the 99 universities in the U.K. The horizontal axis represents the rank obtained using the latent variable method. The universities are positioned on the vertical axis according to their rank, with the top-ranked school at the top of the chart. Thus each point corresponding to the name of a university represents the median rank in that university's posterior distribution of ranks, and the lines extending on either side of that point represent the interval within which the rank would be expected to fall with 95-percent probability.

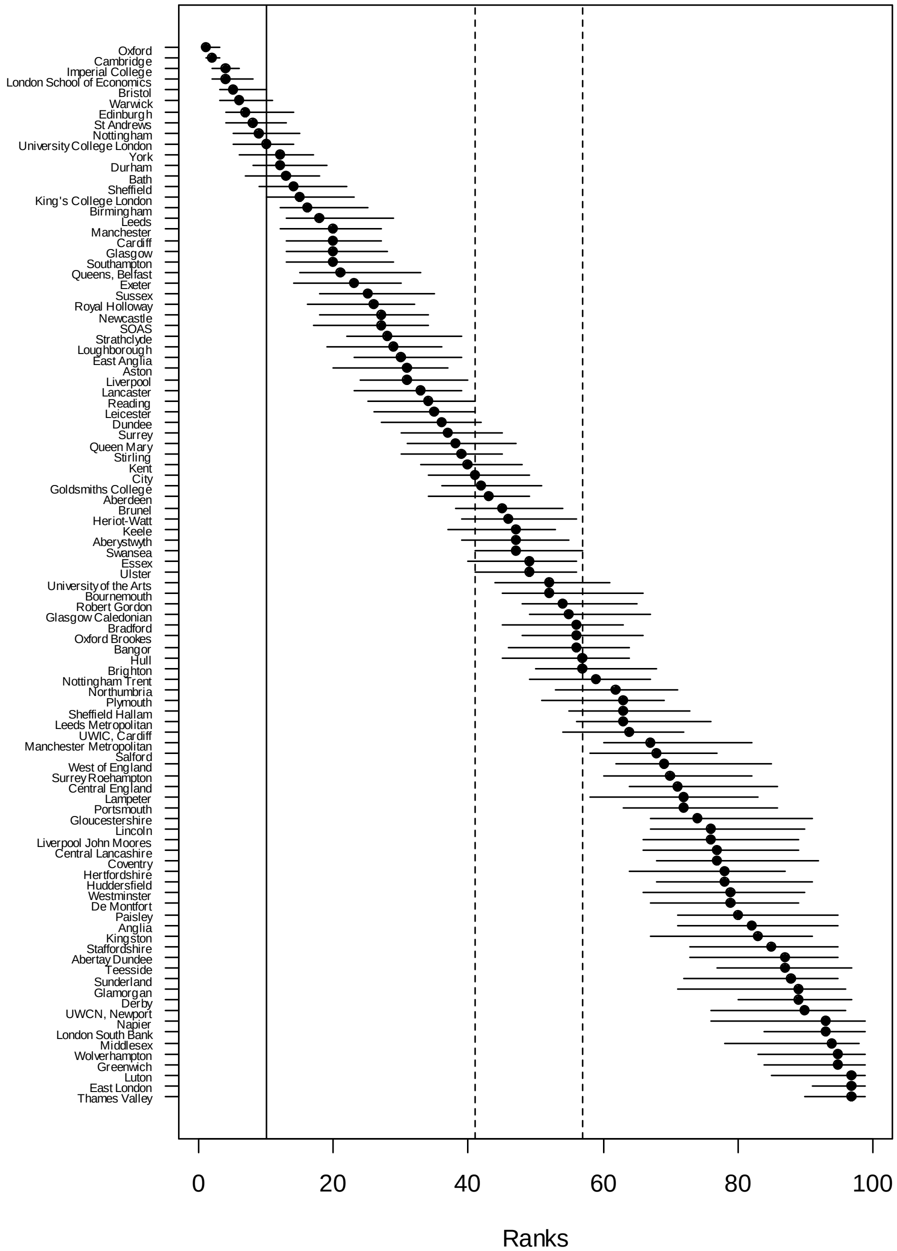

Figure 1: The Distribution of Ranks of U.K. Universities

The solid vertical line drawn at rank 10 helps illustrate the uncertainty associated with these rankings. Only four universities have ranks that are statistically superior (based on the specific measures used to assess quality in this analysis) to 10. This can be seen on the plot by noting that only four schools to the left of the vertical line have probability intervals that do not intersect it. If we wish to compare particular schools, say

Sussex, Swansea, and Northumbria, we can check to see whether their intervals overlap. From the dotted vertical lines that enclose the interval related to Swansea, we see that Sussex is statistically higher in rank to both Swansea and Northumbria, but the latter two universities are not statistically distinguishable. These examples illustrate the point that it is generally not possible to assert that an institution in an ordinal ranking system is of higher quality than all those ranked below.

Also of interest is the size of the probability intervals. At the very top of the rankings, we find that the intervals are noticeably smaller than toward the middle or bottom of the rankings. This tells us that the rankings of those schools are more certain than those in the middle and bottom. Uncertainty expands as we proceed down the rankings and then begins to narrow again slightly towards the bottom.

Table 5 shows the relative influence of the various measures used as inputs in determining the ranking. The table displays the estimated weights and t-statistics associated with the coefficients in the regression equations linking each input measure to the latent variable. We see that the entry standards measure exerts far more weight than other measures.

Table 5. Relative Importance of U.K. University Features in Determining the Ranking

Variable	Weight (w_j)	95% interval	β_1/se(β_1)
Entry standards	0.778	(0.098,3.818)	56.41
Percent high degrees	0.053	(0.043,0.064)	19.24
Research	0.051	(0.042,0.063)	18.54
Completion rate	0.033	(0.025,0.040)	12.05
Teaching	0.023	(0.017,0.030)	8.42
Student-faculty ratio	0.022	(0.016,0.028)	8.11
Graduate destinations	0.018	(0.012,0.024)	6.69
Facilities	0.012	(0.006,0.017)	4.38
Library	0.010	(0.003,0.018)	3.39

Source: Latent variable analysis using data from *The Times Good Universities Guide 2005*

Figure 2 illustrates the relationship between the new rankings and the original rankings reported in *The Times Good University Guide*. In this figure, the horizontal axis again represents the rankings, but this time, the universities are positioned on the vertical axis according to their ranking in *The Times*. The new rankings are again identified by the points and associated intervals, while *The Times* rankings are identified by the short vertical lines (some of these short lines are longer than others to indicate ties). Had the new rankings been identical to those of The Times, all points would have fallen on the lines.

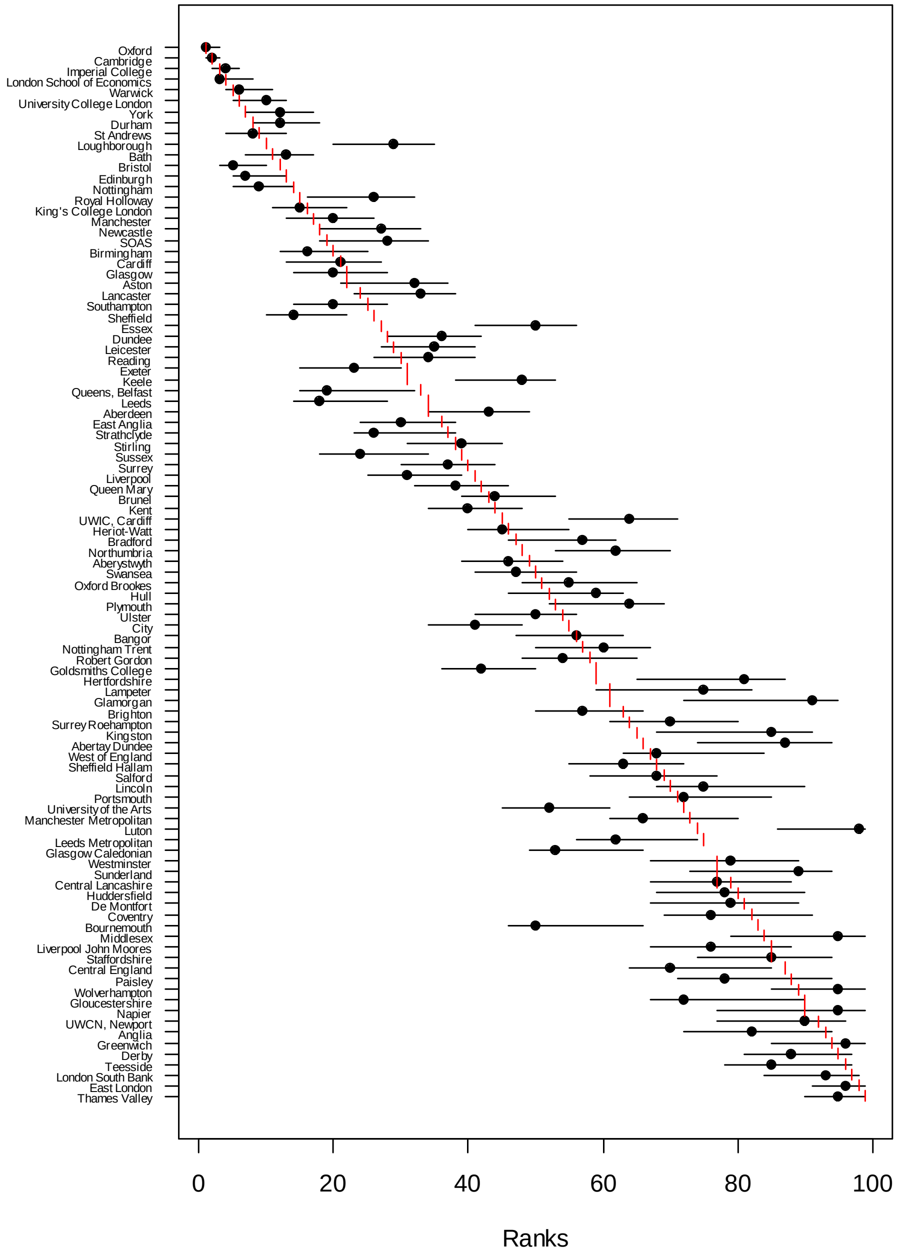

Figure 2: A Comparison of the New Ranks with *The Times* Ranks for U.K. Universities

It is immediately evident that the two ranking systems are quite different. Nearly all points and several entire probability intervals in the new ranking system remain off the lines. The difference between the two sets of rankings is due to the different weighting schemes used.

Results for Research Universities in the U.S.

The next set of figures replicates the above analysis, this time using data on the 129 “top” U.S. national research universities ranked by the *USNWR*. Figure 3 plots the ranks and probability intervals produced by the latent variable analysis and reveals a pattern of uncertainty similar to that seen for the U.K. universities. Due to the size of the plot, we have left off the names. These can be found in the appendix. Again we see that the intervals for universities at the top of the rankings are tighter than those for universities in the middle with some narrowing towards the bottom.

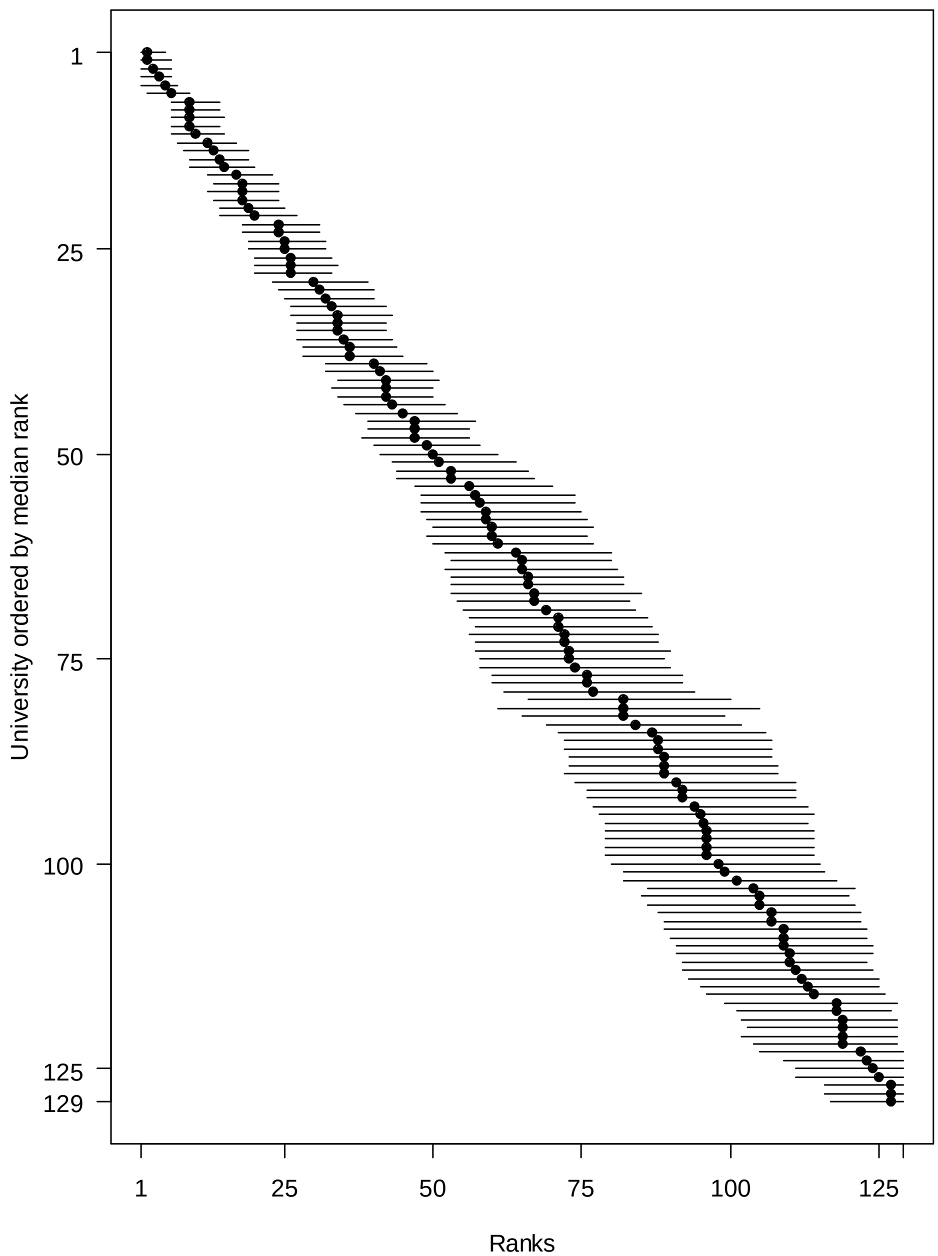

Figure 3: The Distribution of Ranks of U.S. Research Universities

Table 6 indicates the relative importance of the various input measures in determining the overall rankings. The SAT scores are the most powerful drivers of the rankings. Together, student selectivity measures (SAT scores, rejection rate, and the proportion of top 10-percent students) account for a large percentage of the weight.

Table 6: Relative Importance of U.S. University Features in Determining the Ranking

Variable	Weight (w_j)	95% interval	β_1/se(β_1)
SAT at 75th percentile	0.264	(0.204,0.351)	51.44
SAT at 25th percentile	0.165	(0.138,0.195)	38.74
Freshman retention	0.099	(0.082,0.117)	19.89
Rejection rate	0.097	(0.081,0.114)	19.75
Actual 6-year graduation rate	0.095	(0.078,0.112)	19.40
Proportion top 10% students	0.077	(0.063,0.091)	16.37
Peer assessment	0.073	(0.060,0.088)	15.16
Alumni giving rate	0.056	(0.044,0.067)	11.61
Faculty-to-student ratio	0.051	(0.040,0.063)	10.61
Proportion of small classes	0.044	(0.033,0.056)	8.89
Financial	-0.013	(-0.022,-0.005)	-3.60
Graduation rate performance	-0.007	(-0.016,0.003)	-1.40
Proportion of large classes	-0.006	(-0.015,0.004)	-1.19
Proportion of full-time faculty	0.005	(-0.004,0.014)	1.08

Figure 4 illustrates the divergence between the new rankings and the USNWR rankings for the top 50 institutions in the *USNWR* ranking. Again, the new rankings diverge noticeably from the old, and several intervals do not intersect the vertical lines. Thus, we find that the weighting scheme determined by the latent variable method places many universities in different positions from those they occupied in the *USNWR* rankings.

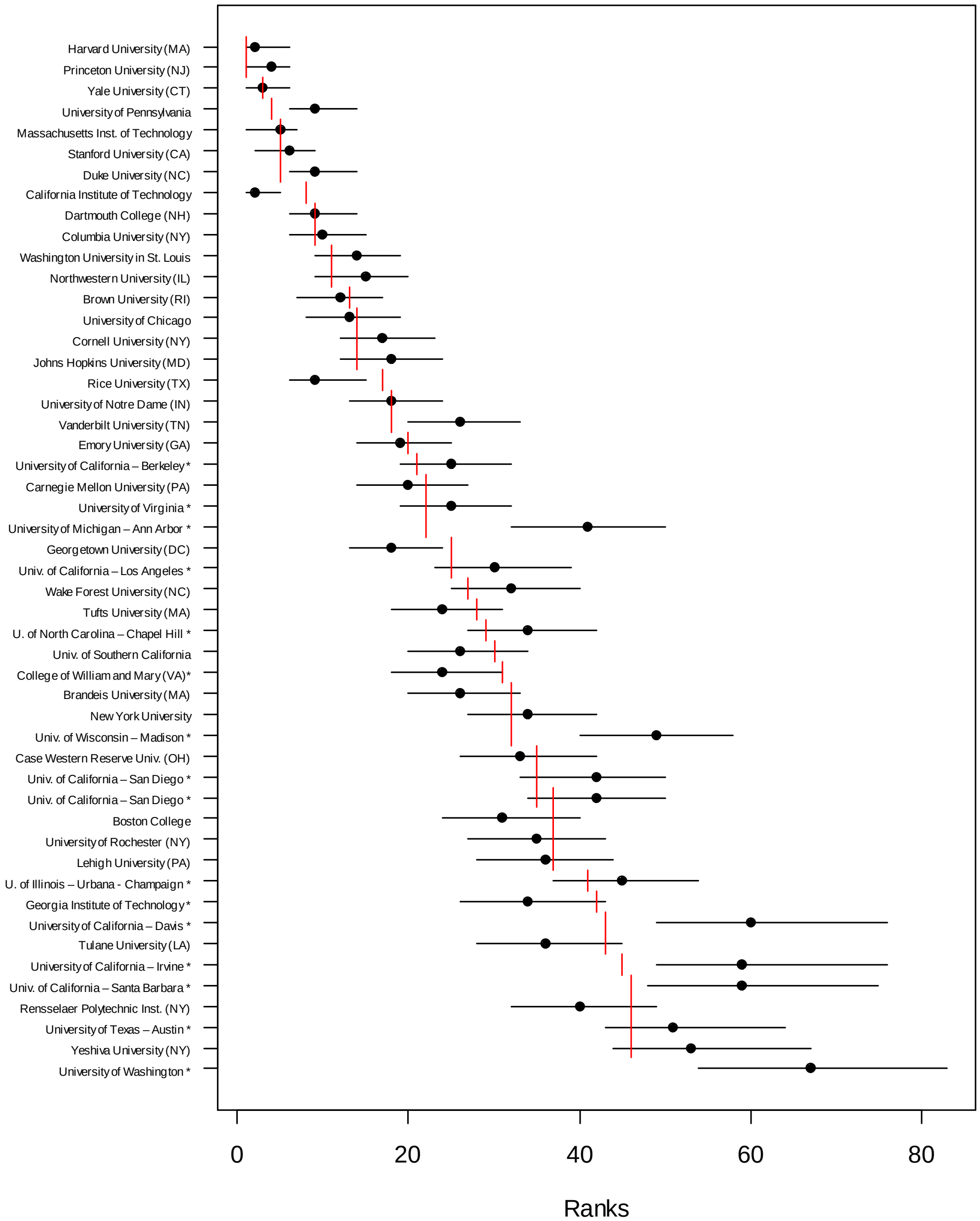

Figure 4: A Comparison of the New Ranks with the *USNWR* Ranks for the Top 50 U.S. Research Universities

Discussion

Using the latent variable method, we have been able to compress the information contained in a set of measures into a single number that captures the relationship of these measures to an underlying "quality" construct. This number is the best expression of the interrelationship of all the measures in the set. The model yields a number for each institution and a set of weights such that if we lost the actual values of the observable measures for a particular institution, we could optimally reconstruct them.

In a weight-and-sum approach, the inclusion of several highly correlated measures of the same underlying construct may inflate the importance of that construct and distort the overall ranking if the total weight assigned to these redundant measures is too large. The latent variable method deals with these correlations differently—in essence, assigning the weights to the various input measures in its simultaneous estimation of their coefficients. Thus, it is less subject to the accusation of "stacking the deck," so to speak, with the addition of redundant measures.

The method shows that student selectivity is a major component of "quality," as expressed in the set of measures used for ranking universities in the U.K. and U.S. The weight given to selectivity is noticeably higher than the weights allowed by *The Times* and *USNWR*. Both rankings systems down-weight the importance of a high-achieving student body and its overall relationship to the other quality measures. Both the US and the UK have selective university systems, however. It is possible that in a country with a less selective university system (e.g., Germany), that this type of measure would not have a high weight in the latent variable analysis.

It might be argued that certain measures *should* be down-weighted. If we have subjective information on the value of particular measures in relation to true quality, the Bayesian framework can readily accommodate such information by encoding it in its choice of prior distributions on the coefficients that form an essential part of the weights.[12] Thus, were there reason to down-weight the influence of, say, selectivity, the proposed method could accomplish this. As a normative question, however, it is important to ask on what theoretical basis these prior suppositions should be made.

Conclusions

The above application of the latent variable approach to the task of differentiating among institutions of higher education provides insights that lead to a greater understanding of the heterogeneity that exists among institutions and perhaps to a greater degree of caution in asserting that certain institutions are of higher quality than others.

The latent variable approach is useful for several reasons. It highlights the degree of uncertainty that exists in the ordinal ranking of universities and permits testing for statistically significant differences among institutions. It highlights the relative importance of particular input measures in the determination of the overall rank. In its divergence from weight-and-sum rankings, it reveals the degree to which different weighting schemes affect the rankings.

The methodology is also subject to limitations. Like standard weight-and-sum ranking systems, it is dependent upon a set of observable quality indicators that may be

[12] Recall that our analysis used non-informative priors.

flawed or incomplete. While this approach may not move us closer a true assessment of the relative quality of education offered at various institutions of higher education, it represents an improvement over traditional systems in its ability to reveal the uncertainty behind rankings and identify where meaningful distinctions can be drawn between one institution and another on the basis of a given set of measures. Thus, it remains a useful tool for those who publish rankings to gain greater insights into the nature of the distinctions they promulgate.

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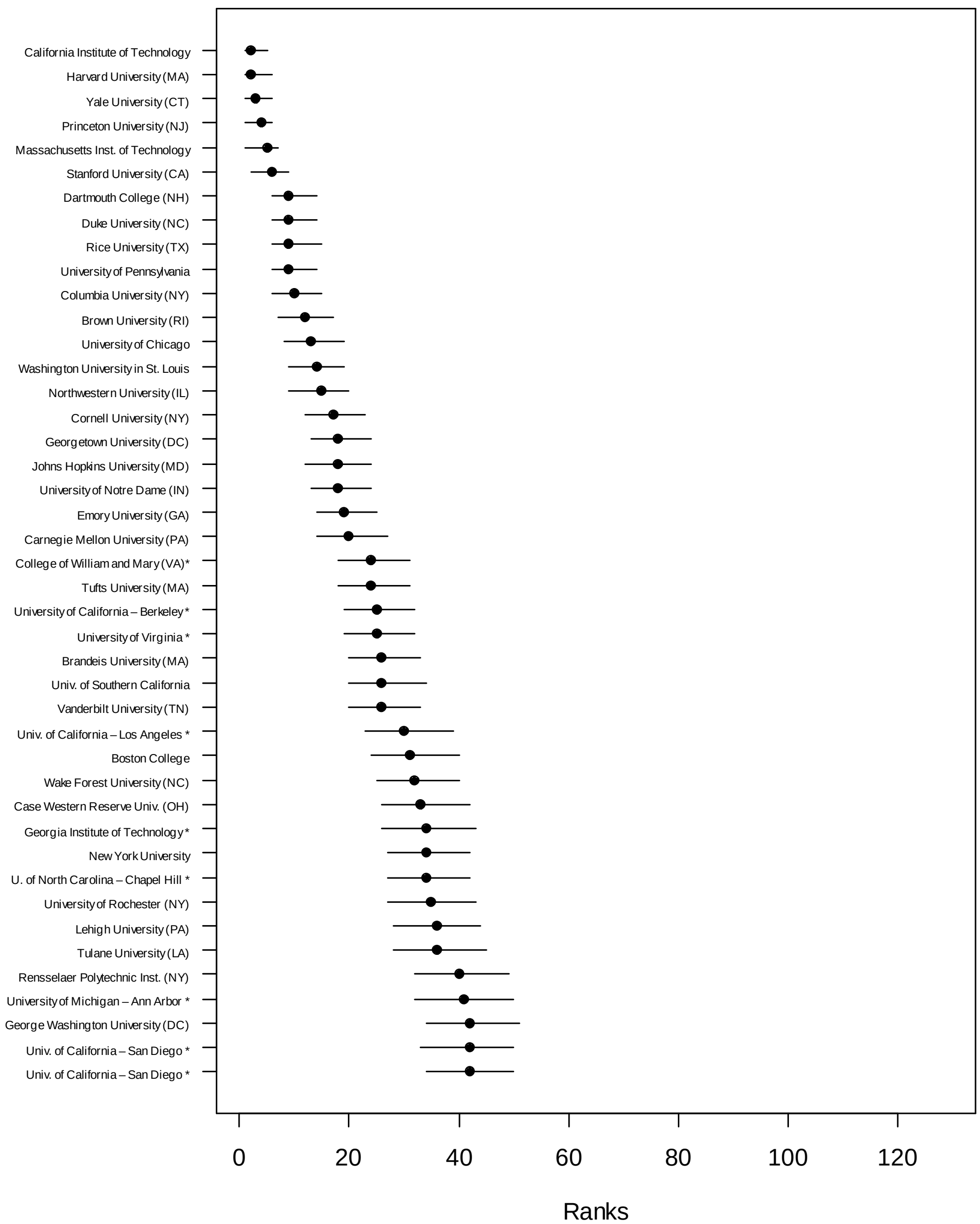
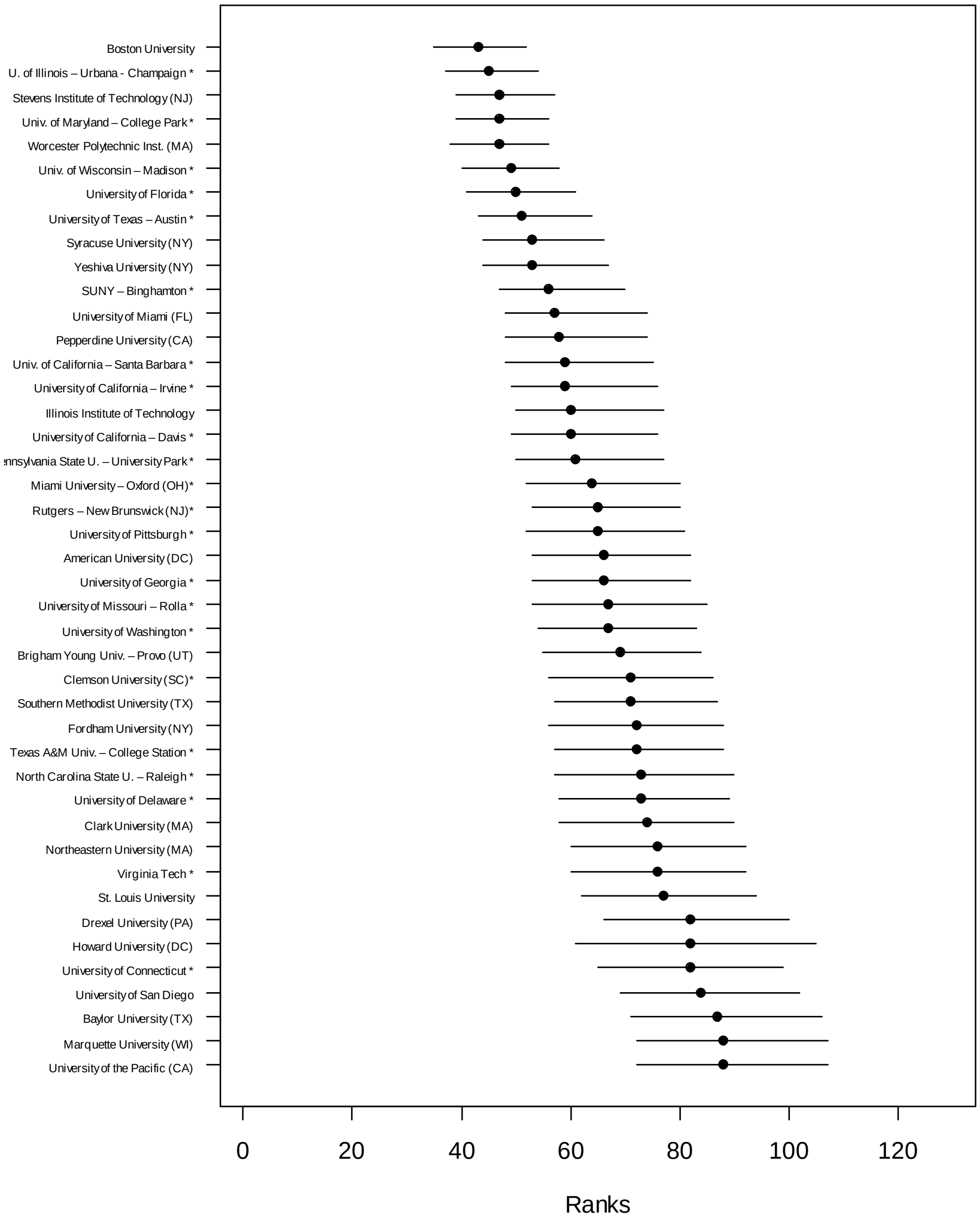
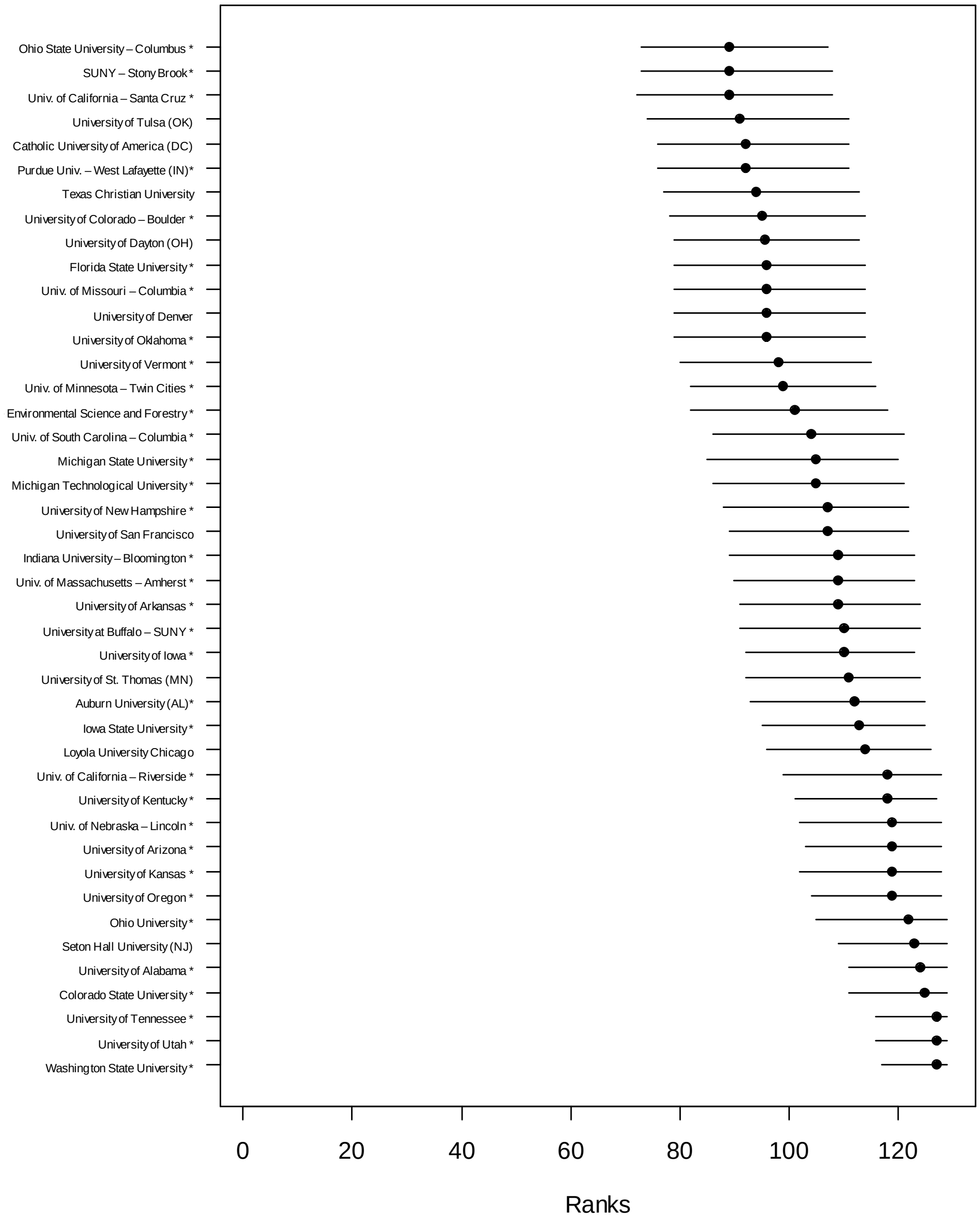
Appendix: The Complete Listing of the Ranks of 129 U.S. Research Universities




Boston University
U. of Illinois – Urbana - Champaign *
Stevens Institute of Technology (NJ)
Univ. of Maryland – College Park *
Worcester Polytechnic Inst. (MA)
Univ. of Wisconsin – Madison *
University of Florida *
University of Texas – Austin *
Syracuse University (NY)
Yeshiva University (NY)
SUNY – Binghamton *
University of Miami (FL)
Pepperdine University (CA)
Univ. of California – Santa Barbara *
University of California – Irvine *
Illinois Institute of Technology
University of California – Davis *
nnsylvania State U. – University Park *
Miami University – Oxford (OH)*
Rutgers – New Brunswick (NJ)*
University of Pittsburgh *
American University (DC)
University of Georgia *
University of Missouri – Rolla *
University of Washington *
Brigham Young Univ. – Provo (UT)
Clemson University (SC)*
Southern Methodist University (TX)
Fordham University (NY)
Texas A&M Univ. – College Station *
North Carolina State U. – Raleigh *
University of Delaware *
Clark University (MA)
Northeastern University (MA)
Virginia Tech *
St. Louis University
Drexel University (PA)
Howard University (DC)
University of Connecticut *
University of San Diego
Baylor University (TX)
Marquette University (WI)
University of the Pacific (CA)
0
20
40
60
80
100
120
Ranks


Ohio State University – Columbus *
SUNY – Stony Brook *
Univ. of California – Santa Cruz *
University of Tulsa (OK)
Catholic University of America (DC)
Purdue Univ. – West Lafayette (IN)*
Texas Christian University
University of Colorado – Boulder *
University of Dayton (OH)
Florida State University *
Univ. of Missouri – Columbia *
University of Denver
University of Oklahoma *
University of Vermont *
Univ. of Minnesota – Twin Cities *
Environmental Science and Forestry *
Univ. of South Carolina – Columbia *
Michigan State University *
Michigan Technological University *
University of New Hampshire *
University of San Francisco
Indiana University – Bloomington *
Univ. of Massachusetts – Amherst *
University of Arkansas *
University at Buffalo – SUNY *
University of Iowa *
University of St. Thomas (MN)
Auburn University (AL)*
Iowa State University *
Loyola University Chicago
Univ. of California – Riverside *
University of Kentucky *
Univ. of Nebraska – Lincoln *
University of Arizona *
University of Kansas *
University of Oregon *
Ohio University *
Seton Hall University (NJ)
University of Alabama *
Colorado State University *
University of Tennessee *
University of Utah *
Washington State University *
0
20
40
60
80
100
120
Ranks