The University Rankings Game:
Modeling the Competition among Universities for Ranking

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ABSTRACT

With university rankings gaining both in popularity and influence, university administrators develop strategies to improve their rankings and pay close attention to the impact of those strategies in the increasingly competitive educational arena. To provide insight into the nature of competition and guidance for the competitors, we develop a model of competition for university rankings that admits localized competition and stickiness of rankings. To address localized competition, we develop an adjacent category logit model that characterizes the log odds unit (i.e., logit) as the ratio of the probability of two adjacent ranks; to address stickiness, our model includes lagged rank as an independent variable. Calibrating our model with data from USNews from 1999-2006 shows persistence in ranking and identifies important interactions among university attributes and persistence in ranking. Our model also outperforms a number of competing models and provides some counter-intuitive implications. The results support the adjacent category logit formulation, showing that on an average with greater than 90% probability a university's rank will be within four units of its rank the previous year. The model can be used to provide (lagged) rank-specific elasticities of ranks with respect to changes in university characteristics, thereby offering input about the likely effect of changes in a university's strategy on its rank.

The [university] system has become "marketized" in the sense that its participants need increasingly to think of themselves in business terms. A whole industry of "enrollment management" consultants has arisen to handle what is ordinarily known as "admissions" and was once quaintly called "crafting a class."

The Atlantic Monthly, Nov 2003, p. 106, "The New College Chaos," James Fallows

1. Introduction

Environmental changes, particularly the recent marked increase in public availability of information, are resulting in the US higher education system becoming more "marketized." In other words, as the quote above illustrates, universities are becoming driven to act like firms in competitive marketplaces, seeking effective competitive strategies. Indeed, as Geiger (2004) notes, "….with nearly 4000 accredited colleges and universities serving more than 15 million students, the US provides a laboratory for higher education [that] has become more market-like over the past quarter century." As a result, competition among universities to enroll students, hire faculty, raise funds, and to improve their position as reflected in rankings published in magazines such as the *U.S. News and World Report's America's Best Colleges* (which we will refer to as USNews), has significantly increased in intensity in recent years. College administrators have increasingly relied on rankings publications such as USNews as marketing tools, since rising college costs and decreasing state and federal funding have forced colleges to compete fiercely with one another for students (e.g., Hossler 2000; Hunter 1995). According to Machung (1998), colleges use rankings to attract students, to bring in alumni donations, to recruit faculty and administrators, and to attract potential donors, all of which are key performance metrics for these institutions. Consistent with these observations, the primary objective of our research is to develop a model of competition among universities for ranking that provides insights into the nature of this competition.

The university sector is not the only domain in which ranking is increasing in importance. Ranking is becoming the hallmark of many industries and economic activities, including product-specific ranked lists from *Consumer Reports*, the Environmental Protection Agency's "Nifty Fifty List" of top chemical polluters, *Playboy* magazine's list of top party schools, the Hot 100 Billboard songs, the BCS college football rankings, among others. In fact a recent search on Google revealed 98.9 million hits for the key word "ranking" (conducted on 18 December 2005); indeed Google itself offers www.googlerankings.com for organizations to obtain rankings of their websites based on key words.

Academics have been paying attention to these ranking issues and have developed models that account for the specific features and context of the ranking process (e.g., Bradlow and Fader 2001; Frey 2005; Mease 2003; Stern 2004; Theoharakis and Skordia 2003). For example, Bradlow and Fader (2001) use the Billboard Hot 100 ranking data to calibrate a generalized gamma latent worth function and develop a Bayesian lifetime model for songs. Other research focuses on how rankings develop (Theoharakis and Skordia 2003 analyze perceived rankings of statistical journals, for example), and on critiquing and suggesting improvements for existing ranking systems, such as the BCS ranking of NCAA Division 1-A college football (e.g., Frey 2005; Mease 2003; Stern 2004). Our analysis focuses on the characteristics and dynamics of a particular ranking system--the university ranking system--and what strategies are most effective for specific schools who seek to better their positions within that system.

University ranks are partly based on institutional resources such as endowments and reputation that normally change slowly. For example, the 1999-2006 lists of USNews top 50 universities include 47 universities that appear throughout. Further, Harvard, Princeton, Stanford, and Yale were in the top five for each year in the eight-year period. Thus, one would expect persistence to exist in university rankings, i.e., lagged rank should contain information concerning current rank. Ranking agencies such as USNews consider university attributes such as alumni giving and selectivity in admissions (for details see Exhibit 1) in their ranking process, but do not explicitly include persistence. Hence, testing for persistence of rankings would provide insights into the stickiness of ranks. As a corollary to the stickiness of ranks, when a school gains in rank, some other school must lose; if ranks are sticky, the schools most likely to lose are those with similar ranks. Hence, competition for ranks tends to be localized, where change in rank (i.e., gain or loss in rank) happens in one or a few ranks at a time. For example, for the above-mentioned eight years of USNews data, the average absolute change in rank in a one-year period was 1.53, suggesting that competition is localized among similarly ranked universities. For instance, a university ranked 25th is unlikely to compete with the university ranked 5th or 45th, but would more likely compete with the universities ranked 24th and 26th. Recognizing this localized nature of competition among universities, we develop an adjacent category logit model that addresses interactions among university attributes (listed in Exhibit 1) and persistence in ranking (e.g., Goodman 1983; Simon 1974).

Our results from the adjacent category logit model demonstrate persistence in university ranking and localized competition. The persistence of ranking results show that lagged rank is a key driver of current rank and that lagged rank interacts in a strategically important manner with university attributes such as academic reputation, financial resources, and faculty resources. For example, we find that investing effort in improving the academic reputation ranks results in greater change in rank for lower ranked schools (Rank 40) than higher ranked schools (Rank 10). The results also support the localized nature of competition among universities for ranking, where the competition is primarily among similarly ranked schools. For example, the top ranked university has a .965 probability of finishing in the top five the next year, whereas the second ranked university has a probability of .937 of ending up in the top five the next year.

We proceed as follows. In the next section we provide an historical overview of university rankings and show that universities actively compete for rankings. Then we specify our adjacent category logit formulation as a model of the ranking process. Next, we present our methodological approach, i.e., data sources, operationalization of variables, alternative model specifications, and estimation approach. Then we discuss our results, which demonstrate the significance of persistence in rankings and the localized nature of the competition for rankings. Our model indicates that most major effects of strategic variables act not as main effects, but rather as interactions with the (lagged) rank variable, providing university-specific guidance of the leverage a university can get by changing its strategic posture on its rank. We conclude by discussing the implications of our research and possible directions for further research.

2. Historical Overview of University Ranking

Much of the recent research on university performance and related strategic behavior relies in one way or another on published and publicly available ratings data, mostly from USNews. These data have two significant limitations that we note at the outset: they focus on undergraduate rankings and include only the most prestigious institutions. Hence, most of these analyses largely ignore other university missions (research output and graduate education) and develop results that may not be applicable to the college and university population as a whole. Nonetheless, undergraduate education is undoubtedly a critical objective of all such institutions and these schools represent a highly visible and influential subset of the entire population.

While academic rankings of U.S. colleges and universities first appeared in the 1870s, their audience then was initially limited to groups such as higher education scholars and professionals, and government officials (Stuart 1995). College and university rankings gained mass appeal in 1983, when USNews, using a survey of college and university presidents, published its first rankings of the undergraduate academic quality of colleges and universities. In 1987, USNews adopted its current multidimensional methodology, aggregating more objective attributes as reported by the universities along with assessments by academic leaders of their peer institutions. Current ratings fall into several categories of student and faculty attributes as well as institutional resources to attain college and university goals as described in Exhibit 1.

[Insert Exhibit 1 Here]

When USNews first introduced its college issue, the publication ranked the top-25 national universities and top-25 national colleges. In 1998, USNews expanded its rankings of the national colleges and universities to the top-50 schools in each category. In the 2004 ranking, USNews created three categories – national doctoral universities, regional master's universities, and colleges – and began ranking its top tiers in each category. The latest version – the 2006 issue – ranks 120 national doctoral universities and 104 national liberal arts colleges.

Prior to 2003, college guides were the primary alternatives to USNews in the popular-press university-rating industry. These annual guides, such as *Barron's Guide to Colleges* and *Peterson's Guide to Four Year Colleges*, while offering much of the same descriptive information as USNews, do not rank universities. Rather, they categorize schools by degree of selectivity. Attesting to the popularity of the USNews ranking, two national publications – *The Atlantic Monthly* and *The Wall Street Journal* – introduced college and university rankings in 2003. While *The Atlantic Monthly* uses a methodology similar to that of USNews, *The Wall Street Journal* bases its rankings on the placement of college and university graduates in top business, law, and medical schools. (Volkswein and Gruing 2004, provide a more complete description and critique of the history, use, and abuse of university rankings).

Hence, the US News undergraduate rankings are the oldest and the most widely used benchmarks for relative school performance and have been used in recent years to support research into the effect of changes in USNews ranks on the number of applicants, matriculation, entering-class quality, tuition, and financial aid (Avery, Fairbanks, and Zeckhauser 2003; Monks and Ehrenberg 1999). Monks and Ehrenberg (1999) found that a drop in rank leads a university to accept a greater percentage of applicants, a smaller percentage of its acceptance pool matriculates, its entering class is of lower quality, and it offers more financial incentives to attract applicants. Tuition rates, however, are unaffected (presumably because list-price tuition is seen as a signal of quality).

Avery et al. (2003) analyze the practice of early admissions and early decision (with early decision, universities will accept candidates prior to the regular round of admission, but candidates need not commit to attend the university) and find that universities favor early decision and early action candidates in their admissions decisions. Thus, for identical candidates, a university is more likely to accept the early admission candidate than the candidate who applies in the regular round of consideration. By favoring early applicants in admissions decisions, the university can increase yield, accept fewer regular-round applicants, and decrease acceptance rates, attributes that are elements of USNews rankings for the period of our analysis.

Thus, it appears that university administrators, while sometimes criticizing the existence of published rankings, especially the numerical rankings such those of USNews, recognize that these rankings are publicly visible performance scorecards and both act and react accordingly. For example, Hobart and William Smith College fired a senior vice president in 2000 after she failed to submit fresh data to USNews, resulting in a major drop in the College’s rank (Graham and Thompson 2001) And even winners see problems as Richard Beeman, Dean of the College of Arts and Sciences at the University of Pennsylvania, in a letter to the New York Times (Sept 17, 2002) commented "…I breathed a sigh of relief when my university continued to appear in the [USNews] top 10." And winners in the ranking game publicize that fact broadly on their websites and other communications materials (for example, see http://www.dukenews.duke.edu/2005/03/usnews0305.html)

3. The Adjacent Category Logit Model for University Ranking

Our model is based on the recognition that (1) university ranks are fairly sticky and difficult to change and (2) any change (i.e., gain or loss in rank) will happen in incremental steps, i.e., one or a few ranks at a time. We specify our model as follows. Let:

- $u = 1 \ldots U$ as the total number of universities that were ranked for every year in the observation period.
- $t = 1 \ldots T$ as the number of time period for which we observe the university ranks ($T = 8$ in our sample).[1]
- $r = 1 \ldots R$ as indexing ranks, where for top 50 schools that we study $R = 50$.
- $X_{ut} =$ the matrix of explanatory variables for university u at time t. (These variables are the ones used by USNews and are described in Exhibit 1.)
- $\pi_r =$ the probability of observing rank r, such that $\pi_r \geq 0$, $\forall\ r = 1 \ldots R$ and $\sum_{r=1}^{R} \pi_r = 1$.

We define the log-odds unit (LOGIT), as adjacent categories such as r and $r+1$, such that the adjacent-categories logits are (e.g., Goodman 1983; Simon 1974):

$$\text{(1)} \qquad \text{logit}\left[\frac{P(Y_{ut} = r \mid X_{ut}, Y_{u(t-1)})}{P(Y_{ut} = (r+1) \mid X_{ut}, Y_{u(t-1)})}\right] = \log\left(\frac{\pi_r(X_{ut}, Y_{u(t-1)})}{\pi_{r+1}(X_{ut}, Y_{u(t-1)})}\right)$$

where, Y_{ut} is the response (rank) for the university u at a given year t and

$\pi_r(X_{ut}, Y_{u(t-1)}) = P(Y_{ut} = r \mid X_{ut}, Y_{u(t-1)})$.

[1] In our analysis we only consider universities that were in the top 50 for each year in the eight-year (1999-2006) period. As statistically it is fairly easy to incorporate the unbalanced panel, this choice of a inclusion was driven by strategic considerations… GARY. Further, note that universities that only appear in the ranking for a sort period are ranked low (typically 47-50 range) and thus do not influence the results in any meaningful manner.

Based on the log odds unit definition in Equation 1, one can define the logit for any two non-adjacent ranks r and R as:

$$\text{(2)} \qquad \log\left(\frac{\pi_r(X_{ut}, Y_{u(t-1)})}{\pi_R(X_{ut}, Y_{u(t-1)})}\right) = \sum_{i=r}^{R} \log\left(\frac{\pi_i(X_{ut}, Y_{u(t-1)})}{\pi_{i+1}(X_{ut}, Y_{u(t-1)})}\right)$$

The log odds ratio in Equation 2 represents a special case of the very flexible baseline-category logit model (e.g., Agresti 2002). Specifically for R ranks, the R^{th} rank can be seen as the baseline category and the log odds $\forall\ r = 1, 2, \ldots R-1$ is given as $\log\left(\frac{\pi_r(.)}{\pi_R(.)}\right)$. To incorporate explanatory variables, the logarithm can be specified as a linear function of the explanatory variables including lag of rank so as to account for persistence in university ranking (e.g., McCullagh 1980):

$$\text{(3)} \qquad \log\left(\frac{\pi_r(X_{ut}, Y_{u(t-1)})}{\pi_R(X_{ut}, Y_{u(t-1)})}\right) = \alpha_r + Y_{u(t-1)}\beta_r + X_{ut}\gamma_r + Y_{u(t-1)}X_{ut}\delta_r$$

As is the case in logit models with multiple categories or ranks, $\pi_r(X_{ut}, Y_{u(t-1)})$ is then defined as:

$$\text{(4)} \qquad \pi_r(X_{ut}, Y_{u(t-1)}) = P(Y_{ut} = r \mid X_{ut}, Y_{u(t-1)}) = \frac{\exp(\alpha_r + Y_{u(t-1)}\beta_r + X_{ut}\gamma_r + Y_{u(t-1)}X_{ut}\delta_r)}{1 + \sum_{r=1}^{R-1} \exp(\alpha_r + Y_{u(t-1)}\beta_r + X_{ut}\gamma_r + Y_{u(t-1)}X_{ut}\delta_r)}$$

The probability specification in Equation 5 leads to the familiar likelihood function (L):

$$\text{(5)} \qquad L = \prod_{u=1}^{U}\prod_{t=2}^{T}\prod_{r=1}^{R} [\pi_r(X_{ut}, Y_{u(t-1)})]^{I_{utr}}$$

where, I_{utr} is an indicator function that equals 1 if $Y_{ut} = r$, else it equals 0.

(Note that as we model lag of rank as an explanatory variable in the likelihood function specification in Equation 6, $t = 2, \ldots T$)

The baseline category logit model specified in Equations 3-5 does not recognize the hierarchy inherent in the ranking. The adjacent category logit recognizes this hierarchy to specify $\beta_r = (R-r)\beta$ and $\gamma_r = (R-r)\gamma$, thereby resulting in re-specification of Equation 3 as:

$$\log\left(\frac{\pi_r(X_{ut}, Y_{u(t-1)})}{\pi_R(X_{ut}, Y_{u(t-1)})}\right) = \alpha_r + (R-r)Y_{u(t-1)}\beta + (R-r)X_{ut}\gamma + (R-r)Y_{u(t-1)}X_{ut}\delta \tag{6}$$

It can be easily seen from Equations 1, 2, and 6 that one can state:

$$\log\left(\frac{\pi_r(X_{ut}, Y_{u(t-1)})}{\pi_{r+1}(X_{ut}, Y_{u(t-1)})}\right) = \alpha_r + Y_{u(t-1)}\beta + X_{ut}\gamma + Y_{u(t-1)}X_{ut}\delta \tag{7}$$

Once parameter estimates are available by maximizing the logarithm of Equation 5 with $\pi_r(X_{ut}, Y_{u(t-1)})$ specified in Equation 6, Equations 6 and 7 can be used to understand the probability of change in rank, i.e., the odds of change in rank from r to $r + p$ are given as:

$$\frac{\pi_r(X_{ut}, Y_{u(t-1)})}{\pi_{r+p}(X_{ut}, Y_{u(t-1)})} = \exp(\alpha_r + pY_{u(t-1)}\beta + pX_{ut}\gamma + pY_{u(t-1)}X_{ut}\delta) \tag{8}$$

With $Y_{u(t-1)} = r$ modeled as an explanatory variable, we can use Equation 8 to calculate the probability of $Y_{ut} = r + p$, $\forall\ p = 0, 1, 2\ldots,\ \forall R = 1,\ldots R\text{-}1$. We now discuss our methodology.

4. Method

4.1. Data Sources and Variable Operationalization

We use ranking data that is published annually by USNews to identify strategies that universities pursue. As noted in Exhibit 1, USNews publishes the overall ranking of the top universities along with subrankings on key aggregated attributes: academic prestige rank, graduation and retention rank (they combine these two raw scores into a single rank), selectivity rank, faculty resources rank, financial resources rank, and alumni giving rank (we refer to these six aggregated attributes as subranks).[2] USNews uses the weights in Exhibit 1 to combine the scores on these six subranks into an overall rank. Thus, from the perspective of university management, to gain in the USNews rankings, a university must invest in improving on one or more of the six subranks. Clearly, a gain in overall rank for a university implies some other university (or universities) is losing rank(s) (a constant sum game). Thus, the strategies (intentional or unintentional) that universities follow are reflected in changes in their subranks. For example, one university may decide to improve its faculty while another may focus on the graduation and retention subrank. Accordingly, one university's faculty resources subrank improves and its graduation and retention subrank worsens, while the other university's subranks move in the opposite directions. Note that while we are not able to observe the absolute level of investment by a university, we assume that what drives a university's competitive position is its relative level of investment (reflected well, we believe, in the subranks) rather than its absolute level.

We use eight years of data from USNews--1999 to 2006--of the top-50 universities to identify competitive strategies (note that as we model lag rank as an explanatory variable, we only have seven years of usable data). Although USNews has published data since 1983, it sometimes changes its methodology substantially, with the last such change occurring in 1999, when USNews moved from a four-point to five-point scale in its peer assessment survey. We view this as a major change to methodology because the survey is the only component of the

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[2] USNews reports the academic prestige score and not the rank. As the report provides ranks for the remaining five attributes, we converted the score to ranks so as to be consistent across the variables. For each of the six subranks, U.S. News scores universities on one or more attributes. For example, in determining selectivity subranks, two of the attributes used by U.S. News are the math and verbal SAT scores of the 25th and 75th percentile student of the entering freshman classes as well as the ratio of applicants accepted to total applicants. U.S. News reports only a partial list of the attribute scores of the universities. Furthermore, U.S. News only partially discloses its function it uses to calculate both the university scores in each of the six categories and the overall score. Not having the U.S. News methodology, we chose to calculate the overall ranks as a weighted average of the six subranks. U.S. News offers its partial description at http://www.usnews.com/usnews/edu/college/rankings/about/index_brief.php

academic reputation subdomain. Accordingly, the first year we chose to include in our analysis is 1999. Finally, we consider only universities that were in the top-50 rankings for the eight-year period (1999-2006) in the analysis. Thus, we retained data on 47 universities giving us a sample size of 329. We present the descriptive statistics for the ranks and subranks for the 329 data points in Table 1.

[Insert Table 1 about here]

4.2. Alternate Model Specification

It is important to test the viability of the proposed model (which we call M_H, Equations 4-6) against alternate model specifications to ensure that (1) the model is not over-specified in the sense that a constrained version of the proposed model outperforms the unconstrained model, and that (2) we have incorporated all important explanatory variables such that the proposed model does not suffer from omitted variable bias. Thus, we first specified two configurations that are nested in the hypothesized model given in Equation 7: (1) we modeled only lag of rank as the explanatory variable (M_{H-2}: i.e., $\gamma = 0; \delta = 0$) and (2) we did not introduce the interaction terms between lag of rank and the subranks (M_{H-1}: i.e., $\delta = 0$). These two models help us to test whether introducing subranks and interactions among subranks and lagged rank explains variance in ranking above and beyond the variance explained by lagged rank. Second, recognizing that the effect of missing variables can be modeled as unobserved, we sought to investigate various models that incorporate unobserved heterogeneity. Specifically, we estimated two models that incorporated time-specific and university-specific fixed effects (e.g., Greene 2003). We present the re-specification of Equation 7 for these two forms of fixed effects as follows (represented as M_{H+1} and M_{H+2}, where λ_t represents time specific fixed effects and ϕ_u represents university-specific fixed effects):

(9) $$\log\left(\frac{\pi_r(X_{ut}, Y_{u(t-1)})}{\pi_{r+1}(X_{ut}, Y_{u(t-1)})}\right) = \alpha_r + Y_{u(t-1)}\beta + X_{ut}\gamma + Y_{u(t-1)}X_{ut}\delta + \lambda_t$$

(10) $$\log\left(\frac{\pi_r(X_{ut}, Y_{u(t-1)})}{\pi_{r+1}(X_{ut}, Y_{u(t-1)})}\right) = \alpha_r + Y_{u(t-1)}\beta + X_{ut}\gamma + Y_{u(t-1)}X_{ut}\delta + \phi_u$$

Finally, we incorporated unobserved heterogeneity by examining the possibility of multiple regimes (i.e., latent segments; Dayton and MacReady 1988). Thus, in this model, M_{H+3}, not only the intercept term, but also the effect of explanatory variables can vary across regimes or latent segments. The model for *S* regimes or latent segments is given as (where θ_s represents the mixing proportions such that $\theta_s \geq 0$, $\forall$ s = 1… *S* and $\sum_{s=1}^{S}\theta_s = 1$):

(11) $$\log\left(\frac{\pi_r(X_{ut}, Y_{u(t-1)})}{\pi_{r+1}(X_{ut}, Y_{u(t-1)})}\right) = \sum_{s=1}^{S}\theta_s[\alpha_{rs} + Y_{u(t-1)}\beta_s + X_{ut}\gamma_s + Y_{u(t-1)}X_{ut}\delta_s]$$

We use a logit specification for θ_s, i.e., $\theta_s = \dfrac{e^{\tau_s}}{1+\sum_{s=1}^{S-1} e^{\tau_s}}$, τ_s $\forall$ $s = 2, \ldots S$ is the constant term that determines the probability of belonging to a regime. We estimated the model in Equation 11 by increasing the value of *s* one increment at a time as long as model fit improved (Dayton and MacReady 1988).

We estimated all models by maximizing the logarithm of the likelihood function. In the case of M_{H+3} we used multiple (50) random starting values to select the optimal solution.

We will use minimum value for Consistent Akaike Information Criterion (CAIC) as a model selection criterion; for nested models the CAIC results are consistent with likelihood ratio tests; e.g., Bozdogan 1987). We calculate CAIC as (*LL* – log-likelihood, *K* – Number of Parameters, *N* – Sample Size):

(12) $$CAIC = -2 * LL + K * (1 + \ln(N))$$

5. Results

5.1. Model Selection

In Table 2 we present the fit statistics for various model configurations discussed earlier along with the description of these models. The hypothesized model (M_H: CAIC = 1209.8), outperforms the model with lag of rank as the only explanatory variable (M_{H-2}: CAIC = 1644.4) and the model that does not include the interactions among the subranks and the lag of rank (M_{H-1}: CAIC = 1469.9). These results were confirmed by likelihood ratio tests and demonstrate the merits of modeling subranks and the interactions among subranks and lag of rank. The hypothesized model also outperforms the two fixed effects model, i.e., time-specific fixed effects (M_{H+1}: CAIC = 1225.4) and university-specific fixed effects (M_{H+2}: CAIC = 1247.8), and the model with two regimes or latent segments (M_{H+3}: CAIC = 1400.0). Thus, after accounting for the explanatory variables, unobserved heterogeneity does not appear to be an issue.

[Insert Table 2 about here]

5.2. Influence of Explanatory Variables

In Figure 1 we present the plot of for the values of rank specific intercept term (i.e., α_r). The figure shows that the intercept term is well behaved in that similar ranks have values for the intercept term closer to each other than for dissimilar ranks. In Table 3 we present the coefficient estimates for lag of rank, subranks, and the interactions among the lag of rank and subranks. Foremost, the results seem to support the persistence of rank hypotheses. Specifically, we find that the lagged rank positively influences the current rank ($p = .0807$, $p < .01$). This finding is consistent with Model M_{H-2}, where we modeled only lag of rank as the explanatory variable and found support for reputation persistence ($b = .1402$ $p < .01$).

[Insert Figure 1 and Table 3 about here]

In terms of subranks, we find that the main effect of academic reputation ($b = -.320$, $p < .01$) is moderated by lagged rank such that academic reputation is more leverageable (i.e., effective for changing rank) for universities with higher rank number (e.g., Rank 50 is of higher rank number than Rank 49) than universities with lower rank number ($b = .0050$, $p < .01$). We find similar results for graduation and retention rank ($b = .0018$, $p < .01$), faculty resources rank ($b = .0004$, $p < .05$), and selectivity rank ($b = .0012$, $p < .01$), where the interaction between lag of rank and the subrank is positive and statistically significant. In contrast, the interaction between financial resources rank and lag of rank is negative and statistically significant ($b = -.0006$, $p < .01$). This negative interaction suggests that financial resources are more effective for changing rank for lower ranked schools than for higher ranked schools. Finally, the results do not support the influence of alumni giving on rank, as neither the main effect nor the interaction between alumni giving rank and lagged rank is statistically significant.[3]

These results demonstrate that the impact of rank persistence depends on other university attributes. The results also highlight the fact that even though ranking agencies such as USNews use subranks to arrive at the university ranks, modeling rank persistence and interactions among rank persistence and subranks provides insights into the university ranking competition beyond a simple examination of subranks (university attributes).

5.3. Stickiness of Ranks

An issue that motivated our research concerns the stickiness of ranks, i.e., the probability of change in rank given a university's rank in the previous year. For the purpose we used the formulae in Equation 8 and results from the model with lag of rank at the only explanatory

[3] The statistically non-significant results on alumni giving should be interpreted with caution. It is possible that if a university actually reduces emphasis on alumni giving, its rank may drop dramatically, given heavy attention ALL universities place on this attribute. It may be more appropriate to view alumni giving as an important driver, but one that did not emerge as a differentiator in our analysis.

variable (Model M_{H-2}). We present the results for pervious rank 5, 14, 25, 35, and 45 in Table 4 (middle panel of Table 4). These probabilities show the localized nature of competition among the universities. For example, the university ranked 15th has the probability of .048, .057, .114, and .225 to be ranked 11th, 12th, 13th or 14th respectively. In fact the probability of this university is with ±4 of its current rank (15) is .903. Thus, competition for ranks among the universities seems to be localized among similar ranked universities.

[Insert Table 4 about here]

An anomaly evident from Table 4 is that in the case of the 15th ranked university, the probability that the university is ranked 15th the next period is .156, well below the probability that the university would be ranked 14th (p = .225). Similarly, the 15th ranked university has a probability of .119 to be ranked 18th as compared to a probability of .063 to be ranked 16th. Such anomalies are apparent for most of the results displayed in Table 4. These anomalies are an artifact of the USNews approach to dealing with tied ranks. For example, if two universities are both given a rank of 2, the next university is given a rank of 4, skipping the rank of 3. Figure 2 gives the actual distribution of the ranks we used here, which, in principle should be uniform, but empirically are clearly not: for the seven year period from 2000-2006 (we lose 1999 as discussed earlier) the frequency of any rank ranges from 1 to 14. Thus, the estimated probabilities reflect this empirical reality that, due to ties, some ranks have high frequency of occurrence and others have low frequency of occurrence. To mitigate the effects of these tied ranks, we broke ties randomly and re-estimated the probabilities – these adjusted results are shown in the panel on the right in Table 4. As can be seen there, the probability estimates are better behaved when ties are removed.

[Insert Figure 2 about here]

6. Discussion

Our model of university ranking reveals a marked persistence in ranking, even when one models the subranks that USNews uses to arrive at that ranking. Of key importance, we observe that persistence interacts in meaningful ways with the subranks, suggesting strategies that different universities might use to improve their ranking. In Figure 3 we plot the interactions among subranks and lagged rank. In Panel A of Figure 3 we present the effect of subranks on rank when lagged rank equals 10 and in Panel B of Figure 3 we present the same effect when lagged rank equals 40 (do note that the scale of the Y-axis is different for the two panels in Figure 3). The upward sloping curves in the two panels suggest that as subranks improve so does the rank (note on both the x and y axes, a higher number means a poorer position than does a lower number). For the school ranked 10, financial resources and graduation and retention are the top two subranks (Panel A of Figure 3), whereas for a school ranked 40, academic reputation and graduation and retention are the two critical subranks (Panel B of Figure 3). In contrast, alumni giving and selectivity subranks appear to be the least important subranks for a school ranked 10 (Panel A of Figure 3), while for a school ranked 40 alumni giving and financial resources are the least important subranks (Panel B of Figure 3). These results demonstrate that, irrespective of a school's rank, it should emphasize graduation and retention and should not expect much return (in terms of increases in rank) by increasing emphasis on alumni giving. However, a highly ranked school gets more leverage from growing financial resources while lower ranked schools get more leverage from improvements in academic reputation. Similar insights are evident from Figure 3 on other subranks.

[Insert Figure 3 about here]

In Figure 4 we show the interaction between lagged rank and four important university subranks to provide insights into the nature of these interactions. For financial resources (Panel A of Figure 4) we see that gain in the financial resources subrank (from 40 to 10) benefits a higher ranked school (Rank 10: change in y-axis from .307 to 1.228) more than a lower ranked school (Rank 40: change in y-axis from .127 to .508). The results differ for the other three subranks, i.e., academic reputation (Panel B of Figure 4), graduation and retention (Panel C of Figure 4), and faculty resources (Panel D of Figure 4). For these subranks (such as in the case of the academic reputation subrank (ACAD); Panel B of Figure 4), change in subrank is more important for a lower ranked school (Rank 40: change in y-axis for ACAD (Panel B) from 1.680 to 6.720) than for a higher ranked school (Rank 10: change in y-axis for ACAD (Panel B) from .180 to .720). For the last two subranks (graduation and retention and faculty resources) even though the gain in subrank helps the lower ranked school more than the higher ranked school, the benefits from improving these subranks are also evident for the higher ranked school (Rank 10). These results demonstrate that a university's current rank helps determine the attribute it should emphasize and allocate resources to in order to get the most leverage in improving that rank.

[Insert Figure 4 about here]

Our analysis also calculates the probability that a university can attain a certain rank given its current rank. In Table 4 we present these probabilities for a wide range of ranking possibilities, showing that competition among universities for ranking is largely localized. Let us focus on the competition among the very top universities, the subject of a recent bestselling book (Karabel 2005). To provide insights into this issue we report the probability of a university ranked in the top 9 given it is ranked in top 5 the previous year (Table 5). For the period from 2000-2006, 49 universities were ranked in the top 5 (again larger than 35 (7 * 5) due to tied ranks). Of these

Harvard, Princeton, Stanford, and Yale made it to the top 5 in each of the seven years; MIT and University of Pennsylvania were there for six of the seven years; Cal Tech was in the top 5 for five years; and Duke was in the top 5 for four years. For this elite group, (Table 5), the probability of losing rank is fairly low (as seen by the probability of being ranked from 6 to 9). The top ranked university has a .375 probability of retaining the top position and .207 probability of coming in second. For the top ranked university a top five rank is a near certainty, with a probability of .965. The second ranked university has a probability of .291 to improve its rank, a probability of .185 to maintain its rank, and a probability of .937 of ending up in the top 5 the next year. As one would expect, the probability of finishing in the top 5 steadily declines as we move from rank 3 to 5, from .890 to .708. (As we did in Table 4, in the panel on the right of Table 5, we report the re-estimated probabilities after breaking ties – here again the probabilities become better behaved).

[Insert Table 5 about here]

Our findings on localized competition and persistence of ranking, including interactions between persistence and university attributes, suggest that strategies that aim to incrementally improve university ranking are potentially effective. Further research is needed to better understand what tactics that support those strategies might be. Normative research, perhaps couched in a decision theoretic or a game theoretic framework, could also provide insights into the interactive nature of the competition among universities for ranking. We also hope that our approach to studying university competition will prove useful for those interested in other domains of competition for ranking, such as the J.D. Power and Associates vehicle ranking and the NY Times best seller list rankings.

In conclusion, we hope our research provides insight into the structure and nature of the competition amongst universities for rankings and what universities might consider doing to most cost-effectively maintain or improve their positions in the rankings universe.

Table 1
Descriptive Statistics and Bivariate Correlation Coefficients

Variable Name	RK	ACAD	GRAD	FAC	SEL	FIN	ALUM
Rank (RK)							
Academic Reputation Rank (ACAD)	.84						
Graduation and Retention Rank (GRAD)	.79	.58					
Faculty Resources Rank (FAC)	.67	.32	.44				
Selectivity Rank (SEL)	.82	.69	.63	.50			
Financial Resources Rank (FIN)	.64	.48	.37	.52	.38		
Alumni Giving Rank (ALUM)	.59	.29	.54	.51	.44	.32	
Mean	23.49	23.80	25.26	35.40	26.08	31.78	47.95
Standard Deviation	13.61	14.80	16.64	34.65	19.26	27.59	52.02

NOTES: Statistics are presented for N = 329 (U = 47, T = 7) data points. All correlation coefficients were statistically significant ($p < .01$). Multicollinearity did not seem to be an issue as the highest condition index was 28.94 less than the cutoff of 30 (Greene 2003); also in incremental model building (i.e., introducing explanatory variables one at a time), we did not observe any sign changes in statistically significant coefficients.

Table 2
Model Selection

Model Name	Model Description	Number of Parameters	Log-Likelihood Value	CAIC
$\mathbf{M_{H-2}}$	Lag rank as the explanatory variable.	50	-701.2	1644.9
$\mathbf{M_{H-1}}$	Lag rank and main effects of subranks as the explanatory variables.	56	-599.1	1469.9
$\mathbf{M_{H}}$	Lag rank, main effects of subranks, and interaction between lag of rank and subranks as the explanatory variables***.* *(Our main model)***	62	-454.6	**1209.8**
$\mathbf{M_{H+1}}$	M_H with unobserved heterogeneity modeled as time-specific fixed effects.	68	-447.8	1225.4
$\mathbf{M_{H+2}}$	M_H with unobserved heterogeneity modeled as university-specific fixed effects.	108	-362.0	1247.8
$\mathbf{M_{H+3}}$	M_H with unobserved heterogeneity modeled as latent segments, i.e., two latent segment version of $M_{H.}$	125	-369.8	1400.0

NOTES: CAIC – Consistent Akaike Information Criterion. CAIC value in bold indicates model selected.

Table 3
Results from the Adjacent Category Logit Model (M_H)

Variable Category	Variable Name	Coefficient (Standard Error)
Rank Persistence	Lag of Rank (LR)	.0807** (.0200)
Subranks	Academic Reputation (ACAD)	-.0320** (.0130)
	Graduation and Retention Rank (GRAD)	.0061 (.0105)
	Faculty Resources (FAC)	.0136 (.0084)
	Selectivity (SEL)	-.0090 (.0128)
	Financial Resources (FIN)	.0367** (.0093)
	Alumni Giving (ALUM)	.0022 (.0055)
Interaction between Lag of Rank and Subranks	LR *ACAD	.0050** (.0006)
	LR *GRAD	.0018** (.0003)
	LR *FAC	.0004* (.0002)
	LR *SEL	.0012** (.0004)
	LR *FIN	-.0006* (.0003)
	LR *ALUM	.0002 (.0002)

* $p < .05$
** $p < .01$

Table 4
Probability of Rank Persistence and Change with Current Rank a5 to Rank ab

Probability of Rank a*	Actual Ranks					Ranks with Ties Randomly Broken				
	a = 0	a = 1	a = 2	a = 3	a = 4	a = 0	a = 1	a = 2	a = 3	a = 4
b = 1	.086	.048	.047	.073	.066	.040	.014	.007	.002	.002
b = 2	.083	.057	.066	.128	.055	.058	.029	.016	.005	.007
b = 3	.061	.114	.172	.030	.122	.080	.053	.032	.012	.020
b = 4	.220	.225	.020	.187	.133	.103	.083	.064	.021	.040
b = 5	.257	.156	.302	.163	.310	.124	.115	.087	.044	.087
b = 6	.057	.063	.062	.058	.065	.136	.139	.118	.071	.168
b = 7	.080	.085	.102	.129	.062	.134	.146	.140	.101	.198
b = 8	.035	.119	.096	.128	.108	.117	.134	.145	.128	.240
b = 9	.079	.036	.036	.007	.066	.088	.107	.129	.144	.237

NOTES: The probabilities reported in the left panel are for the model with the lag of rank as the explanatory variable assuming the lag rank equals ab. For example, if a = 0, and b=5, then the probability that the university with rank 5 in year *t-1* has the rank 5 (i.e., b = 0) in year *t* is .257. Similarly, the probability that the university ranked 45 (a = 4, b = 5) in year *t-1* has a rank 44 (a = b = 4) in year *t* is .133. Due to tied ranks (i.e., two or more universities having the same rank) the probabilities do not uniformly decline or increase. To account for the effects of tied ranks, we broke the ties randomly, re-estimated the probabilities and report them in the panel on the right.

Table 5
Probability of Rank Persistence and Change among Top 5 Universities

Current Year Rank	Actual Ranks					Ranks with Ties Randomly Broken				
	Previous Year Rank					Previous Year Rank				
	1	2	3	4	5	1	2	3	4	5
1	.375	.291	.212	.142	.086	.270	.196	.130	.077	.040
2	.207	.185	.154	.119	.083	.223	.187	.143	.097	.058
3	.087	.089	.086	.076	.061	.176	.169	.149	.116	.080
4	.178	.210	.232	.237	.220	.130	.144	.145	.131	.103
5	.119	.161	.205	.241	.257	.089	.114	.132	.137	.124
6	.015	.024	.034	.047	.057	.056	.082	.110	.131	.136
7	.012	.022	.036	.057	.080	.031	.053	.082	.112	.134
8	.003	.006	.012	.021	.035	.016	.030	.054	.085	.117
9	.004	.009	.021	.042	.079	.007	.015	.031	.056	.088
Cumulative Probability of Top 5	.965	.937	.890	.815	.708	.887	.810	.699	.559	.405
Cumulative Probability of Top 9	.999	.997	.993	.982	.958	.996	.990	.975	.942	.880

NOTES: See note on Table 4 for explanation. Again, right panel addresses issues of tied ranks and smoothes out probabilities.

Figure 1

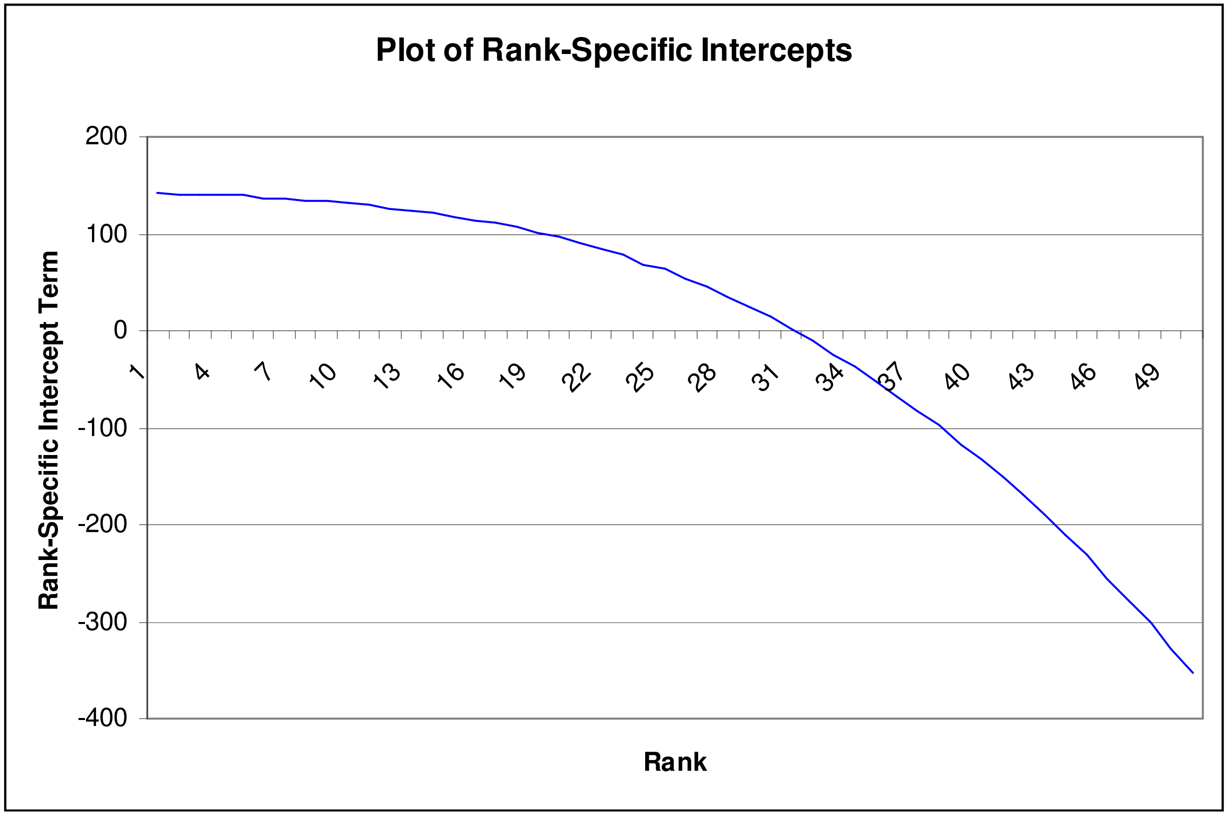

Plot of Rank-Specific Intercepts
200
100
0
-100
-200
-300
-400
Rank-Specific Intercept Term
1
4
7
10
13
16
19
22
25
28
31
34
37
40
43
46
49
Rank

Figure 2
Empirical Distribution of Ranks in the Sample for the Seven-Year Period, Showing the Effect of Tied Ranks

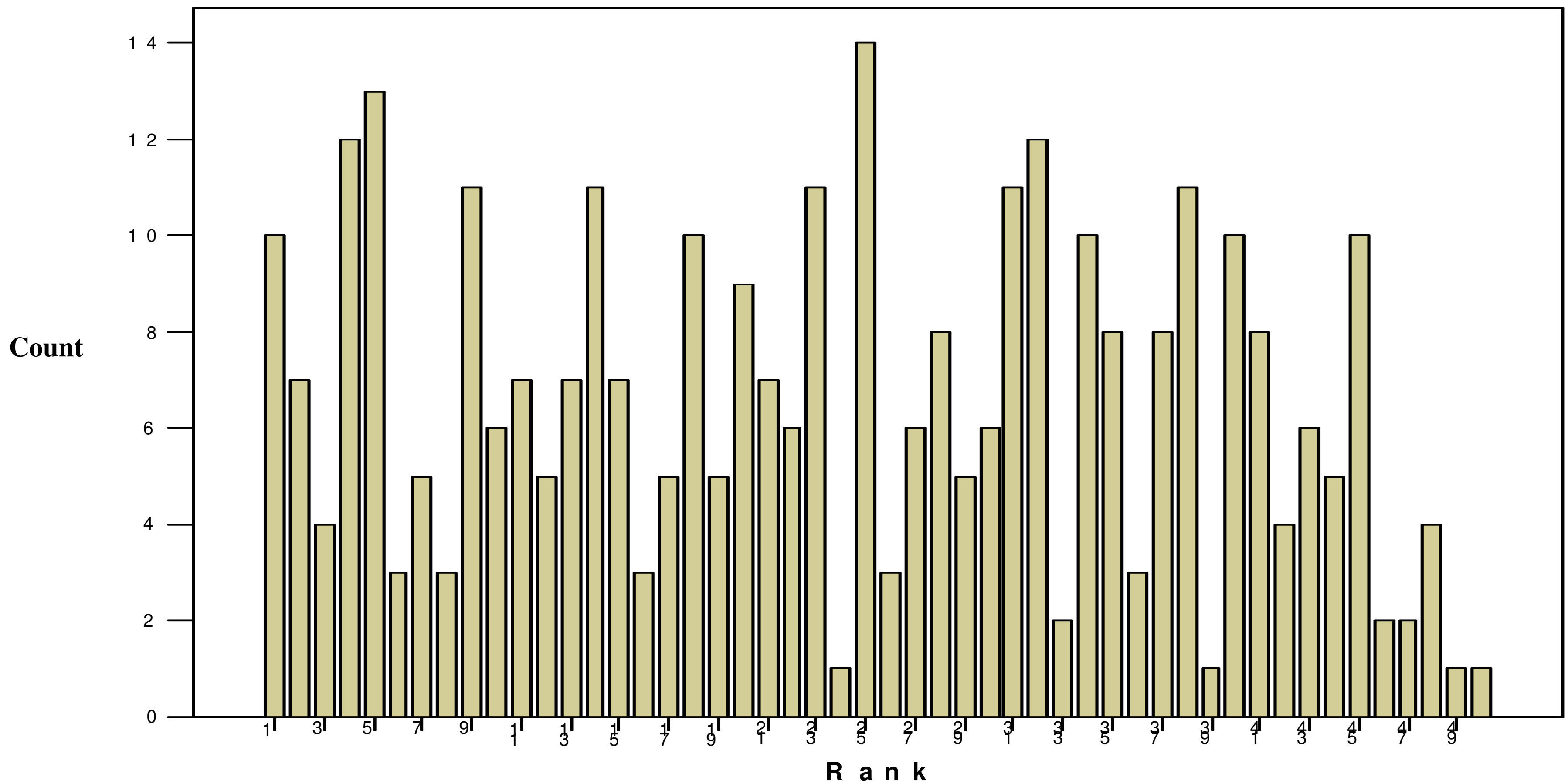
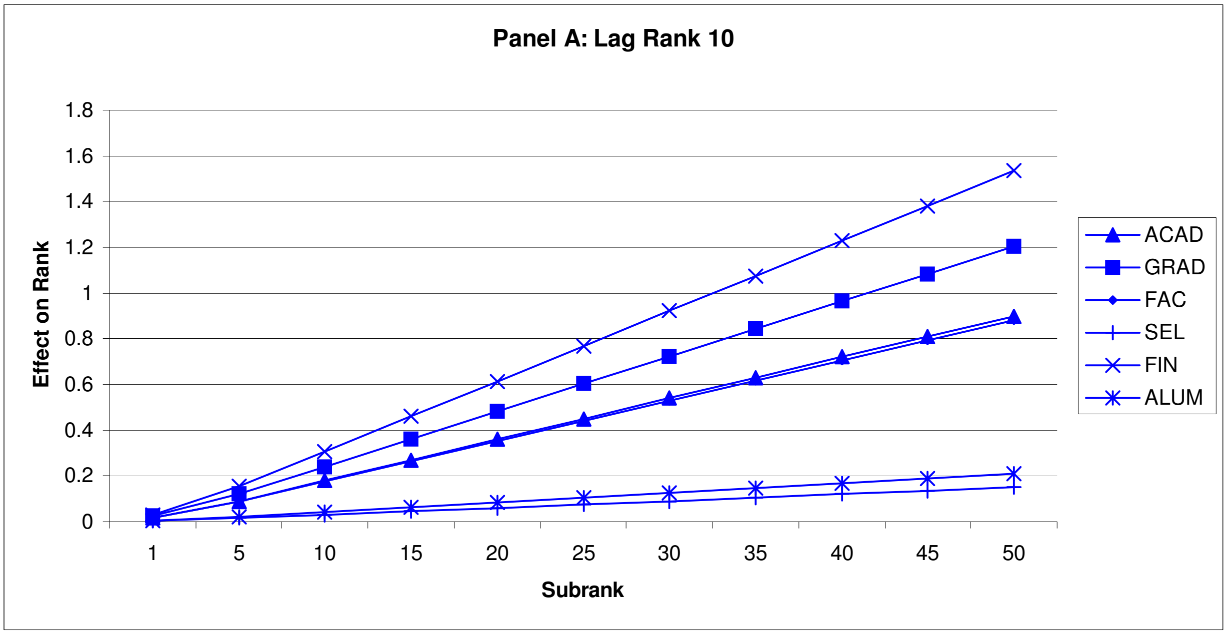
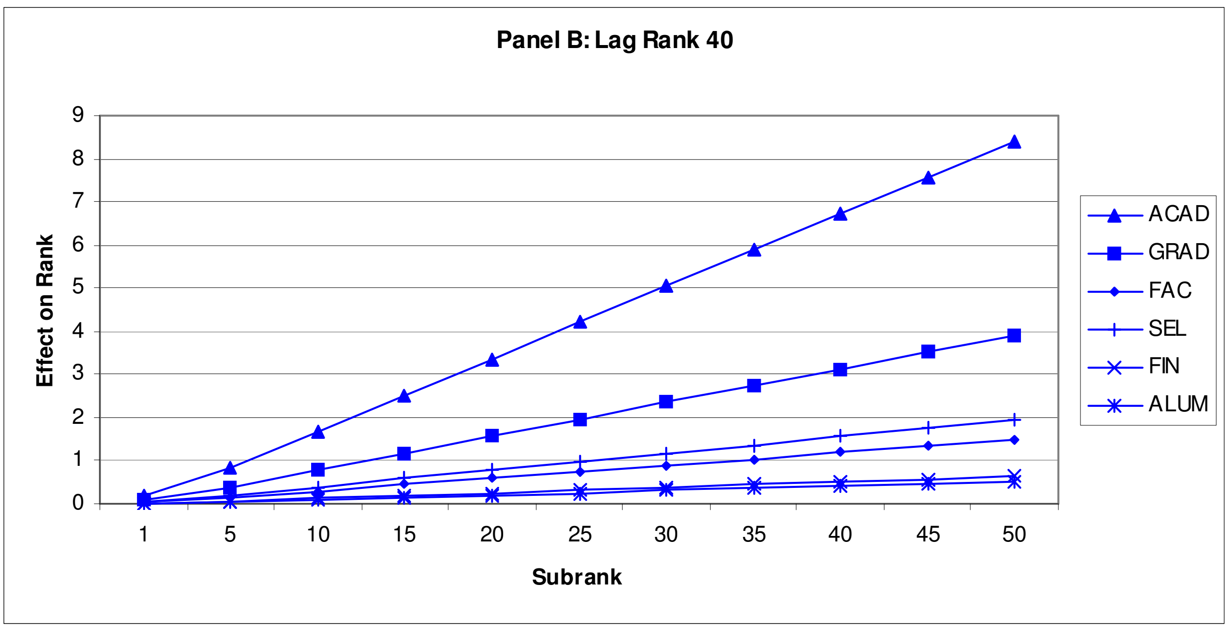


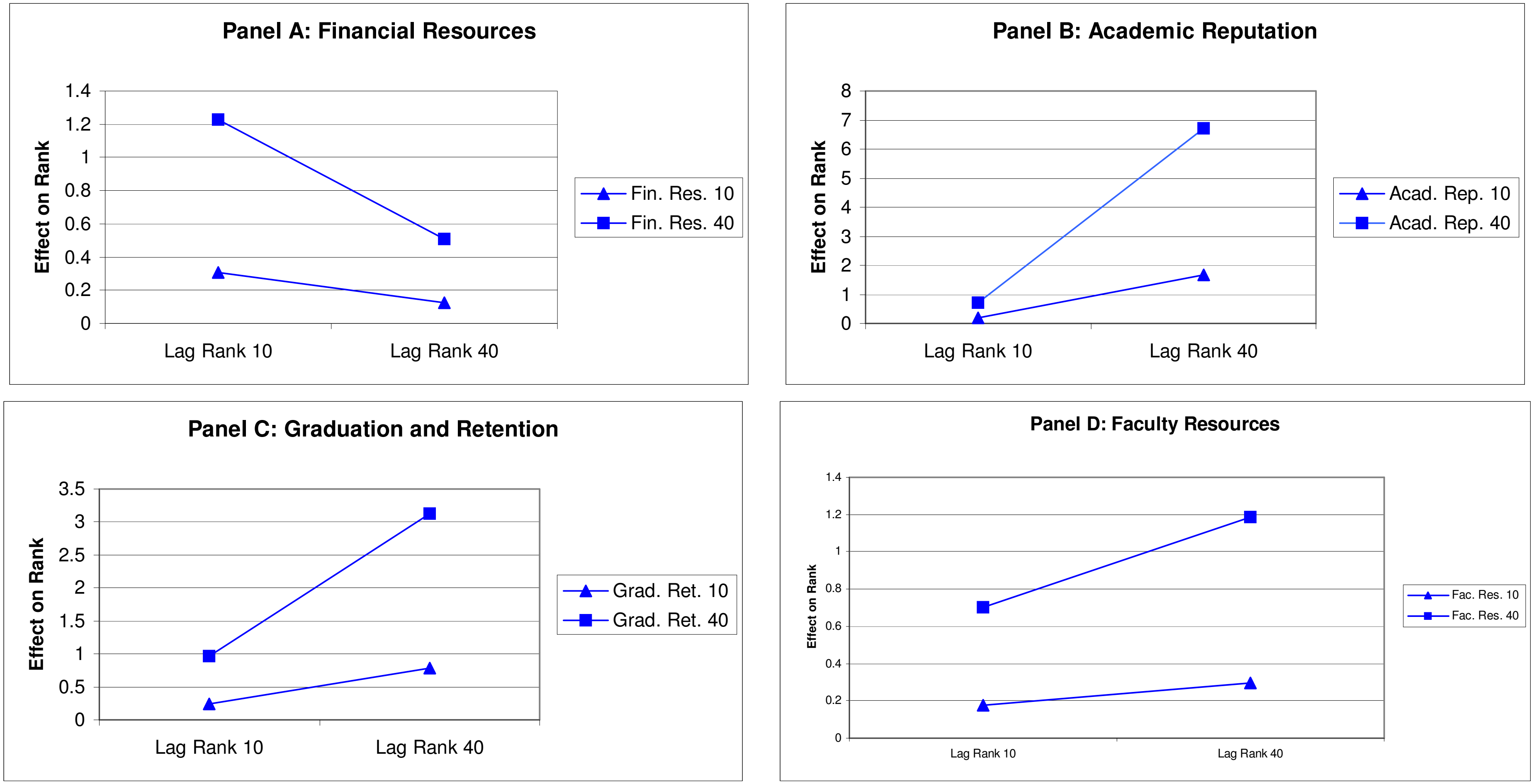
Figure 3
Effect of Lag Rank and Subranks





NOTES: Panel A plots the effect of subranks on rank when lagged rank is 10; in Panel B the same effect is plotted when the lagged rank is 40. These plots show that for better-ranked schools (lagged rank 10), financial resources and graduation and retention subranks are the most important, whereas for lagged rank 40 schools, academic reputation and graduation and retention subranks are the most critical.

Figure 4
Effects of Select Subranks and Lag of Rank



NOTES:	The figure depicts the interaction between lagged rank and four important university attributes to provide insights into the nature of these interactions. For financial resources (Panel A) we see that gain in the financial resources subrank (from 40 to 10) benefits a higher ranked school (Rank 10) more than a lower ranked school (Rank 40). The results differ for the other three subranks, i.e., academic reputation (Panel B of Figure 4), graduation and retention (Panel C of Figure 4), and faculty resources (Panel D of Figure 4) where change in subrank is more important for a lower ranked school (Rank 40) than for a higher ranked school (Rank 10).

Exhibit 1
US News Weights and Definitions:
(Source: http://www.usnews.com/usnews/edu/college/rankings/about/04rank_brief.php)

Peer assessment (weighted by 25 percent). The U.S. News ranking formula gives greatest weight to the opinion of those in a position to judge a school's academic excellence. The peer assessment survey allows the top academics we contact–presidents, provosts, and deans of admission at peer institutions–to account for intangibles such as faculty dedication to teaching. Each individual was asked to rate peer schools' academic programs on a scale from 1 (marginal) to 5 (distinguished). Those individuals who didn't know enough about a school to evaluate it fairly were asked to mark "don't know." Synovate, an opinion-research firm based near Chicago, collected the data; 61 percent of the 4,095 people sent questionnaires responded.

Retention (20 percent in national universities and liberal arts colleges and 25 percent in master's and comprehensive colleges). The higher the proportion of freshmen who return to campus the following year and eventually graduate, the better a school is apt to be at offering the classes and services students need to succeed. This measure has two components: six-year graduation rate (80 percent of the retention score) and freshman retention rate (20 percent of the score). The graduation rate indicates the average proportion of a graduating class who earn a degree in six years or less; we consider freshman classes that started from 1993 through 1996. Freshman retention indicates the average proportion of freshmen entering from 1998 through 2001 who returned the following fall.

Faculty resources (20 percent). Research shows that the more satisfied students are about their contact with professors, the more they will learn and the more likely it is they will graduate. We use six factors from the 2002-03 academic year to assess a school's commitment to instruction. Class size has two components: One represents the proportion of classes with fewer than 20 students (30 percent of the faculty resources score); the second represents the proportion with 50 or more students (10 percent of the score). Faculty salary (35 percent) is the average faculty pay, plus benefits, during the 2001-02 and 2002-03 academic years, adjusted for regional differences in the cost of living (using indexes from the consulting firm Runzheimer International). We also weigh the proportion of professors with the highest degree in their fields (15 percent of the score), the student-faculty ratio (5 percent), and the proportion of the faculty who are full time (5 percent).

Student selectivity (15 percent). A school's academic atmosphere is determined in part by the abilities and ambitions of the student body. We therefore factor in test scores of enrollees on the SAT or ACT tests (50 percent of this factor); the proportion of enrolled freshmen who graduated in the top 10 percent of their high school classes for all national universities-doctoral and liberal arts colleges-bachelor's, and the top 25 percent for institutions in the master's and comprehensive colleges categories (40 percent of the score); and the acceptance rate, or the ratio of students admitted to applicants (10 percent of the score)..

Financial resources (10 percent). Generous per-student spending indicates that a college is able to offer a wide variety of programs and services. U.S. News measures the average spending per student on instruction, research, student services, and related educational expenditures.

Graduation rate performance (5 percent only in the in national universities and liberal arts colleges). This indicator of "added value" was developed to capture the effect of the college's programs and policies on the graduation rate of students after controlling for spending and student aptitude. We measure the difference between a school's six-year graduation rate for the class that entered in 1996 and the predicted rate for the class. The predicted rate takes into account the standardized test scores, among other characteristics, of these students as incoming freshmen, and a variety of characteristics of the school, including the school's expenditures on them. If the actual graduation rate is higher than the predicted rate, the college is enhancing achievement.

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