Association for Institutional Research

PROFESSIONAL FILES | SUMMER 2017 VOLUME

Supporting quality data and decisions for higher education.

Letter from the Editor

Summer brings time to reflect and recharge. The Summer 2017 volume of AIR Professional Files presents four articles with intriguing ideas to consider as you plan for the next academic year.

Association for Institutional Research

Data governance is a pressing issue for many IR professionals, as sources of data proliferate and challenge our ability to control data integrity. In her article, *Institutional Data Quality and the Data Integrity Team*, McGuire synthesizes and interprets results from 172 respondents to an AIR-administered survey of postsecondary institutions on their data integrity efforts. She describes the current state of data governance and offers strategies to encourage institutional leaders to invest in data quality.

Those of us who work in assessment often take it for granted that assessment results will be used for learning improvement. Fulcher, Smith, Sanchez, and Sanders challenge this assumption by analyzing information from program assessment reports at their own institution. *Needle in a Haystack: Finding Learning Improvement in Assessment Reports* uncovers many possible reasons for the gap between obtaining evidence of student learning and using that evidence for improvement. The authors suggest ways to promote learning improvement initiatives, and share a handy rubric for evaluating assessment progress.

Institutional researchers are beset with requests to form peer groups, and it seems that no one is ever satisfied with the results. Two articles in this volume present very different methodologies for forming sets of comparison institutions. In her article, *A Case Study to Examine Three Peer Grouping Methodologies*, D'Allegro compares peer sets generated by different selection indices. She offers guidance for applying each index and encourages cautious interpretation of results. Rather than rummaging around for the perfect peer set, Chatman proposes creating a clone, or doppelganger university, one that is constructed from disaggregated components drawn from diverse data sources. In *Constructing a Peer Institution: A New Peer Methodology*, he walks us through the process of creating peers for faculty salaries, instructional costs, and faculty productivity. While the constructed peer approach has its challenges, the appeal of achieving a perfect fit peer is undeniable.

I hope your summer "reflection" inspires you to share your work with your IR colleagues through *AIR Professional Files*.

Sincerely,

Sharron L Ronco

Sharron L. Ronco

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EDITORS

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ARTICLE 142

Association for Institutional Research

A CASE STUDY TO EXAMINE THREE PEER GROUPING METHODOLOGIES

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About the Author
Mary Lou D'Allegro is associate provost at Paul Smith's College.

Acknowledgments
This paper is an update to a previous study published in *AIR Professional Files:* M. L. D'Allegro and K. Zhou, "A Case Study to Examine Peer Grouping and Aspirant Selection," *Professional Files* (Fall 2013), Association for Institutional Research. The following faculty inspired the author to develop additional novel peer selection indices not noted in previously published studies: Aaron Pacitti, Douglas T. Hickey Chair in Business and Associate Professor of Economics; and John Cummings, Dean of Science and Professor of Physics, both at Siena College. Thank you for intelligent and imaginative approaches in selecting institutional peers.

Abstract
This study considered three selection indices to choose institutional peers: (a) proximity, (b) percentile, and (c) normative. Although conceptually similar, only the proximity selection index had been previously studied. The purpose of this paper is threefold. First, the procedures used to generate the peer sets for each selection index are provided. Second, an empirical investigation was conducted to compare the institutional peers chosen by each selection index using those procedures. Third, the stability of peer selection over time was also ascertained from that enquiry.

Compiled separately from two data sets extracted three years apart, the three selection indices under investigation yielded remarkably different sets of peers. Fewer than half of the institutions used in this study were identified as peers at both points of time. Additional analyses revealed that the underlying distributions of the characteristics used to select peers might be just as influential as the characteristics themselves. The results did not produce sufficient evidence to endorse any one of the selection indices, but instead suggest that a combination of selection indices might be superior to any one selection index alone.

BACKGROUND

The continued increase in public scrutiny of higher education, the expanded demands of accountability, and the overall cynicism of the value of higher education have put colleges and universities on high alert. To counter this skepticism, colleges and schools have increased their efforts to evaluate their quality, efficiency, and effectiveness (Ruben, 2004). A growing and important segment of that evaluation is the comparison and benchmarking to like institutions (Qayoumi, 2012). Therefore, peer selection has become more prevalent. Moreover, higher education has seen the benefit of using peer comparisons and benchmarking to inform decision making and strategic planning.

This research builds on previous work that examined the methodology to choose a set of institutional peers. Specifically, that research investigated the usefulness of the proximity selection index and proposed standardized equation to foster ease of replication. In that work, the proximity selection index was deemed to be an appropriate methodology for the selection of a generic set of institutional peers (D'Allegro & Zhou, 2013). For this research, an institutional peer is defined as institutions that are similar with regard to certain delineating factors (Anderes, 1999; Trainer, 2008). A selection index is a numerical designation system to indicate the extent to which an institution is a potential peer.

Faculty proposed to the researcher two different approaches to peer selection indices that were not considered in the researcher's previously published work. The faculty's suggestions seemed rational because their methodologies might temper potential irregularities in the data. Particularly, their proposed selection indices either (a) relied on statistics that were less susceptible to the perils of non-normal distributions than the standard deviation used in the proximity selection index or (b) standardized the distribution so that imperfections in the data were minimized. As will be discussed in the "Methodology" and "Results" sections, non-normal distributions can acutely affect the set of peer institutions that are selected. This further confirmed that the process for determining peers seems to be arbitrary (Anderes, 1999). Accordingly, there is little or no evidence to the quality or adeptness of many processes to select a set of peers. Careful planning and investigation of the criteria used to select a set of institutional peers is still advised, but the researcher realized the frailty of even the most careful undertaking of selecting a set of institutional peers, including the conclusions of previous research.

At the heart of the paper is the description of three different selection indices and the ensuing peer sets created by each. Those selection indices were similar to the nearest neighbor rationale (McLaughlin, Howard, & McLaughlin, 2011). For all three selection indices, the distance between any given institution or comparison institution and the target institution on predetermined parameters was calculated. The divergence among selection indices is their underlying distributions. Correspondingly, the primary purposes of the study were to: (a) determine and document the differences, if any, in the institutional peer sets produced by each selection index; (b) conclude, from any differences, what index is best; and (c) ascertain the stability of peer selection over time.

METHODOLOGY

This study does not abandon previously applied principles and, as such, uses a variety of sources and methods to maintain a practical balance between stakeholder judgment and statistical analysis (Trainer, 2008). Credibility of the institutional peer sets relies on constituent input. Not only were faculty and staff consulted for this compilation, but in addition the concept for the alternative selection indices arose from the propositioned reasoning of two faculty members. Hence, selection methodologies were based primarily on constituent suggestions and on other documented peer selections.

In the original research, an attempt to find a quick, pragmatic method to choose a set of peers from two or three institutional characteristics was unsuccessful. Using different combinations of those institutional characteristics, it was discovered that the resulting peer sets were similar to the target institution with respect to some data elements but different with respect to others. Those differences were substantial enough to render the selection process ineffectual. This reinforces previous findings that institutional characteristics alone are not sufficient in choosing institutional peers (Shin, 2009).

Instead, a more-informed and more-comprehensive process was tested. The selection process entailed five steps outlined by D'Allegro and Zhou (2013): (a) identifying an initial set of peers, (b) choosing the preliminary set of variables, (c) transforming and standardizing variables, (d) determining the best set of variables to use, and (e) establishing the best selection strategy. This research is fundamentally undistinguishable from that research except for the last step. Therefore, a pithy summary of Steps 1–4 are provided, along with a comprehensive description of Step 5.

1. Identifying an Initial Set of Peers

The initial set of peers was selected a priori to this study. To recap, an initial set of institutional characteristics was identified to eliminate from further analysis institutions that would not realistically be considered a peer of the target institution. The initial set of institutions was chosen from an original list of private, nonprofit institutions that submitted data to the Integrated Postsecondary Education Data System (IPEDS) from the Data Compare Institutions website. The list was generated using the EZ group option (National Center for Education Statistics [NCES], 2012). Data for these institutions were collected for 2010 and 2011; these were the most recent data available at the time of the previous study. An updated data set was identically assembled using 2014 and 2015 information; these were the most recent data available at the time of this study. Note that for the target institution, the 2015 Basic Carnegie Classification did not change from 2010 (Carnegie Foundation, 2015). Furthermore, only the basic 2015 Basic Carnegie Classification was currently available on the EZ group option. Lists for both time periods were generated using the following criteria: (a) private not-for-profit institutions, 4-year or above; (b) highest degree awarded either a bachelor's degree, master's degree, or both; (c) baccalaureate college for arts and sciences, or baccalaureate college balanced arts and sciences, diverse fields; (d) enrolled full-time undergraduate students; (e) institution size between 1,000 and 9,999 students; (f) Title IV participant (federal financial aid eligibility); (h) located in the United States or designated as a U.S. Service School (e.g., U.S. Naval Academy), and (i) not a tribal college. These parameters align with the characteristics of the target institution. This is also on par with selection parameters recommended by previous studies (Anderes, 1999). As a result of applying these criteria, 285 institutions were selected for the previous study while the updated listed yielded 232 institutions.

2. Choosing the Preliminary Set of Variables

Other pertinent information was collected for each of these institutions. Relevance in the context of selecting peers are those data points that indicate the institution's priorities (Anderes, 1999; Cohodes & Goodman, 2012). For the most part, an institution's focus is on quality. As such, the target institution's own Key Performance Indicators (KPIs) were the starting point. KPIs are a mix of approximately 20 output or direct measures of quality and input or influencers of quality. Therefore, the initial set of variables chosen either had some influence on quality or included direct measures of institutional performance. Faculty and staff were also asked to rate the importance of each KPI, being mindful of the importance of using both input and output variables in the peer selection process.

The data also had to be easy to access for all or most institutions. Several sources were considered including: (a) National Survey of Student Engagement (NSSE) benchmarks, (b) American Association of University Professors (AAUP) Faculty Compensation Survey (2012), (c) Noel Levitz Student Satisfaction Inventory (NLSSI), and (d) *U.S. News & World Report* rankings (*U.S. News & World Report*, 2015). Nevertheless, not all institutions participate in the NSSE or NLSSI or administer these surveys within a reasonable time period to avail comparisons. Also, detailed AAUP faculty salary data are not available for many institutions. Consequently, data were obtained from IPEDS or the *U.S. News & World Report* rankings.

The preliminary set of 28 variables are shown in Appendix A, along with the institutional characteristics used to select the initial set of peers. Note that the KPIs have remained the same and, therefore, the faculty were not consulted again for this study. Therefore, no adjustments were needed for the updated data set.

3. Transforming and Standardizing Variables

There was a fair amount of variability in enrollment among the initial set of institutions. Moreover, the enrollment of the target institution was twice the size of most of the institutions in both data sets. Therefore, some of the data elements were standardized to mitigate differences due to institutional size (Gater, 2003; Huxley, 2009). This was accomplished by using the full-time equivalent (FTE) for enrollment as the divisor. Examples of data elements that were standardized by dividing by the FTE included the number of conferred bachelor's degrees, number of applicants, unduplicated annual enrollment, instructional expenses, and endowment.

Full-time and part-time faculty counts were combined into one data element. In effect, the proportion of full-time faculty was calculated by dividing the sum of full-time plus part-time faculty into the number of full-time faculty.

4. Determining the Best Set of Variables to Use

Of the 28 variables identified in Step 2, three were both output measures and among the target institution's KPIs: (a) ratio of conferred bachelor's degrees to FTE, (b) 1-year retention rate, and (c) 6-year graduation rate. These variables were also student centered—specifically student success focused—and aligned with the target institution's mission. To augment the data analysis and simplify its interpretation, the remaining variables were classified into

Table 1. Overall OLS Regression Models for the Three Performance Indicators: Ratio of Conferred Bachelor's Degree to FTE, 1-Year Retention Rates, and 6-Year Graduation Rates

		Standardized
Category	**Variable**	**Beta Coefficient**
Original Data Set		
Ratio of Conferred Bachelor's Degrees to FTE		
Admissions	25th Percentile Mathematics SAT	.348*
Faculty	Average Faculty Salary	–.142
Enrollment	Estimated Fall Enrollment per FTE	–.053
Institutional Characteristics	Selectivity	–.282**
Finance	Instructional Expenses per FTE	.166
1-Year Retention Rates		
Admissions	25th Percentile Mathematics SAT	.465***
Faculty	Average Faculty Salary	.135
Enrollment	FTE	.064
Institutional Characteristics	Selectivity	.301***
Finance	Instructional Expenses per FTE	.065
6-Year Graduation Rates		
Admissions	Percent of Students Receiving Federal Grant Aid	–.145**
Faculty	Average Faculty Salary	.211**
Enrollment	FTE	.090
Institutional Characteristics	Selectivity	.274**
	Proportion of Transfer Students	–.104**
Finance	Total Price of Attendance	.007
	Instructional Expenses per FTE	.224***
Updated Data Set		
Ratio of Conferred Bachelor's Degrees to FTE		
Admissions	Applicants per FTE	–.141*
Faculty	Percent of Faculty with Terminal Degree	.254**
Enrollment	12-Month Enrollment per FTE	.065
Institutional Characteristics	Selectivity	.038
Finance	Total Price of Attendance	.393***

1-Year Retention Rates		
Admissions	75th Percentile Mathematics SAT	.383***
Faculty	Average Faculty Salary	.086
	Percent of Faculty with Terminal Degree	.054
Enrollment	FTE	.131*
	12-Month Enrollment per FTE	–.050
Institutional Characteristics	Selectivity	.130
Finance	Total Price of Attendance	.089
	Alumni Giving Rate	2.229*
6-Year Graduation Rates		
Admissions	75th Percentile Mathematics SAT	.350***
Faculty	Average Faculty Salary	–.015
	Percent of Faculty with Terminal Degree	.127**
Enrollment	FTE	.158***
	12-Month Enrollment per FTE	–.040
Institutional Characteristics	Selectivity	.132*
Finance	Total Price of Attendance	.181**
	Alumni Giving Rate	.202***

Note: $^*p \leq .05$, $^{**}p \leq .01$, $^{***}p \leq .001$.

one of the following five groups: (a) admissions, (b) faculty, (c) enrollment, (d) institutional characteristics, and (e) finance.

As described in our previous research, several regression analyses, single-step ordinary least square (OLS), were used to identify the best variables to select a set of peers. In the first phase, regression models were compiled separately for the five variable categories for each of the three output measures, a total of 15 models. Because the analysis was still exploratory at this stage, the single-step enter method was preferred over other models. Distributing the variables into five groups allowed the inclusion of all variables into the model for that category (SPSS, 2012). Informed by previous research, the standardized beta weights were the determinants of what data elements would be used for peer selection (Hom, 2008).

In the second phase, an overall regression model for each output variable was computed using the best predictor(s) from each of the five regression models. The best predictor(s) had the smallest significance level associated with the standardized beta coefficient. The standardized beta weight's significance level indicates if a variable is, in fact, a predictor of the output variable (Cohen & Cohen, 1983). Although there were some exceptions, only one predictor from each category was chosen for the three overall models. This was deliberate because there were high correlations among predictors in any given category. In addition, the inclusion of only one or two predictors from each category forced a balance of institutional metrics for peer selection. The best predictors for each KPI regression model by category for the original and updated data sets are listed in Table 1.

5. Establishing the Best Selection Strategy

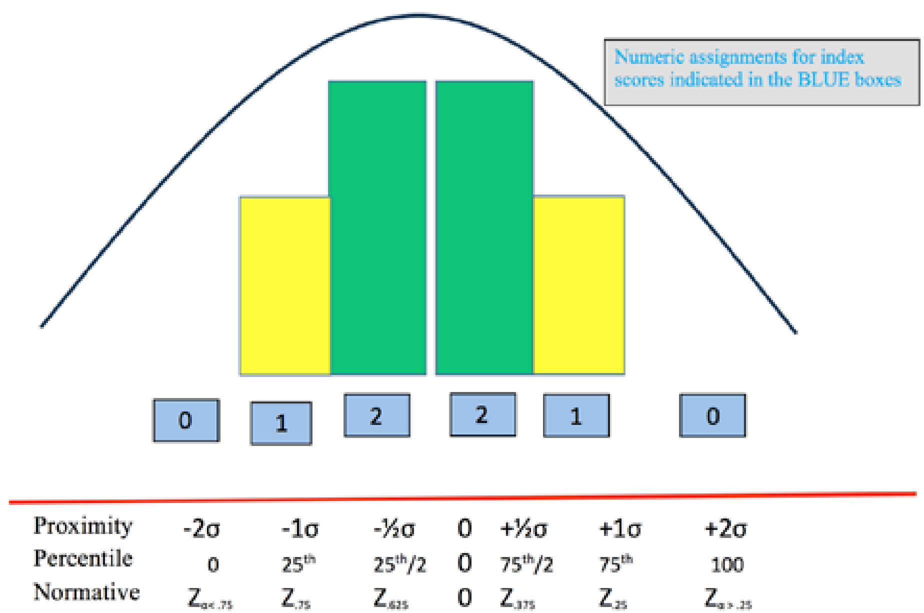
Peer institutions are determined by having metrics that are close to the target institution (McLaughlin et al., 2011). This is manifested in the computation of a selection index. Three selection indices were examined: (a) proximity, (b) percentile, and (c) normative.

The calculation of each selection index also involves several steps but the steps are basically the same for each: (a) identifying the most relevant parameters, (b) computing the numerical difference between the comparison and target institutions on each of those parameters, (c) averaging those differences across parameters, and (d) determining range cut-scores to delineate a peer from an almost-peer. The first step, identifying the most relevant parameters, has already been decided by the three overall OLS models mentioned in Step 4. Descriptions of Steps b–c are provided for each index below. The determination of range cut-scores are further described in the "Results" section.

Proximity selection index

As mentioned, the numeric differences between the target and each comparison institution were computed for each predictor. The mean of these differences determines an institution's propinquity to the target institution. For the proximity selection index, the unit of measurement is the standard deviation for each predictor. This is depicted in Figure 1, with the assumption for this illustration that the underlying data distribution for each predictor is normally distributed. For each predictor, a proximity index score of 1 was assigned to the comparison institution that was between one-half and one standard deviation of the target institution's metric, a score of 2 was given if the comparison institution was within one-half a standard deviation. Equally weighted, the average of the proximity index scores derives the proximity selection index. The two equations that compose the proximity selection index calculation are shown in Appendix B. An example on how to calculate the proximity selection index is provided in Appendix C.

Figure 1. Selection Index Numeric Assignments for Differences Between Target College and Each Institution in the Initial Data Sets



Percentile selection index

For the percentile selection index, differences between the target and each comparison institution were determined for each predictor as it was for the proximity selection index. Moreover, the logic is the same and is shown in Figure 1. However, the boundaries for each percentile index score is determined by the first and third quartile cut-scores, and not by the data distribution's standard deviation as it was for the proximity selection index. In effect, the percentile selection index ensures an equal number of comparison institutions in each partition.

A slight diversion is in order. Normal distributions are not assumed and skewed variables can still produce accurate results (Smith, 2012). Yet, extreme values or outliers on the low end or high end of the distribution can affect or skew the distribution and drag the mean away from a true measure of central tendency. Outliers on both ends might also affect the distribution's kurtosis. Kurtosis refers to the width of the peak of the distribution around the measure of central tendency (Hembree, 2013). In turn, this exaggerated dispersion could unduly increase the standard deviation and, thus, stretch the distribution segments. Consequently, a disproportional number of comparison institutions would receive larger index scores than they deserve because they would be more likely to fall in a subdivision closer to the mean. This might not be a problem per se, but could compromise the ability of the selection index to distinguish a peer from a non-peer.

On the other hand, the percentile selection index distribution is partitioned with an equal number of comparison institutions in each section. Unlike the proximity selection index, outliers are less likely to affect the percentile selection index because the percentile selection index relies on the median as the center of the distribution and not a potentially displaced mean. Therefore, the percentile selection index could be advantageous to the proximity selection index, especially for skewed data distributions.

For each predictor, a percentile index score of 1 was assigned to the comparison institution that was within 25 percentile points of the target institution metric, and a score of 2 was given if the comparison institution was within 12.5 percentile points of the target institution. This is a smaller partition than the proximity selection index, given a percentile index score greater than 0 is awarded if the comparison institution is within 50 percentile points or half the percentile selection index distribution versus approximately 68% of the proximity selection index distribution. Equally weighted, the average of the percentile index scores derive the percentile selection index. The two equations used for computing the percentile selection index are shown in Appendix B. An example of how to calculate a percentile selection index is provided in Appendix C.

Normative selection index

Before the boundaries for each normative selection index were established, values for each predictor were converted to z-scores. Each predictor was standardized with the resulting distribution having a mean of 0 and standard deviation of 1 (SPSS, 2012). That said, the standard normal distributions were derived from using the original distribution's mean and standard deviation. Therefore, effects of the outliers and resulting asymmetrical distributions were not completely eradicated. However, the advantage of these transformed distributions is the fact that the new distributions were symmetrical. In essence, the normative selection index is a hybrid of both the proximity and percentile selection indices. As with the proximity selection index, the mean and standard deviation determine distance or probability. However, as with the percentile selection index, the use of the standard normal distribution, ensures that the distribution is sectioned into equal parts.

Another benefit of transforming the original distribution to the standard normal distribution is that the cut-points are easier to compute and conceptualize. As mentioned, the curve created by the z-scores represented by the x-axis and resulting probabilities plotted on the y-axis, in a standard normal distribution is symmetrical (Weiss, 2015). The difference in the proportion of the total area under the curve that is to the right of the z-score between the comparison institution and target institution was used to determine distance from the target institution.

For each predictor, a normative index score of 1 was assigned to a comparison institution that was within one-fourth the distance of the total standard normal distribution's area from the target institution. As with the percentile selection index, a score of 2 was given if the comparison institution was within one-eighth of the area or distance from the target institution's probability corresponding to the z-score. Equally weighted, the average of the normative index scores derives the normative selection index. The equations used to compute the normative selection index are shown in Appendix B. An example on how to calculate a normative selection index is provided in Appendix C.

RESULTS

For the original data set, there were 58 peers and 47 almost-peers across the three peer selection indices. There were fewer peers in the updated data set, 34. There were 55 almost-peers. Across data sets, the normative selection index in the original data set produced the largest number of peers, 51. The percentile selection index in the

Table 2. Index Score Peer and Almost-Peer Classifications for the Three Selection Indices

Selection Index	Peer		Almost-Peer	
	N*	Percent**	N*	Percent**
Original Data Set				
Proximity	813	65.6%	426	34.4%
Percentile	638	53.8%	547	46.2%
Normative	756	60.7%	487	39.3%
Updated Data Set				
Proximity	750	60.1%	498	39.9%
Percentile	595	64.5%	327	35.5%
Normative	606	60.2%	400	39.8%

*Note: * Count of index scores for each predictor for each peer and almost-peer.*
*** Percent of index scores that were 1 (Almost-Peer) or 2 (Peer).*

updated data set produced the fewest number of peers, 26, just slightly more than half the size of the largest set of peers or set of almost-peers.

Selection Index Ranges

Proximity selection index

For the original data, the range of the resulting proximity selection index was 1.33 to 1.78 for the peers and almost-peers. The updated data set posted a range that was slightly more compressed, ProxI Range = 1.44 to 1.78, for the peers and almost-peers. The cutoffs for the peer set was the 95th percentile, while the almost-peers were institutions between the 90th and 95th percentiles.

The set of proximity peers and proximity almost-peers changed between the original data set and the updated data set. In part this was due to the smaller set of initial peers in 2016 compared to 2013 (N = 285, N = 232, respectively). The smaller number of initial peers in the updated data set was the result of several circumstances. For 46 of the original data initial set of institutions, the Basic Carnegie classification level changed in 2015 to a master's level. The enrollment of six of these original data set initial institutions dropped below 1,000, and one institution closed.

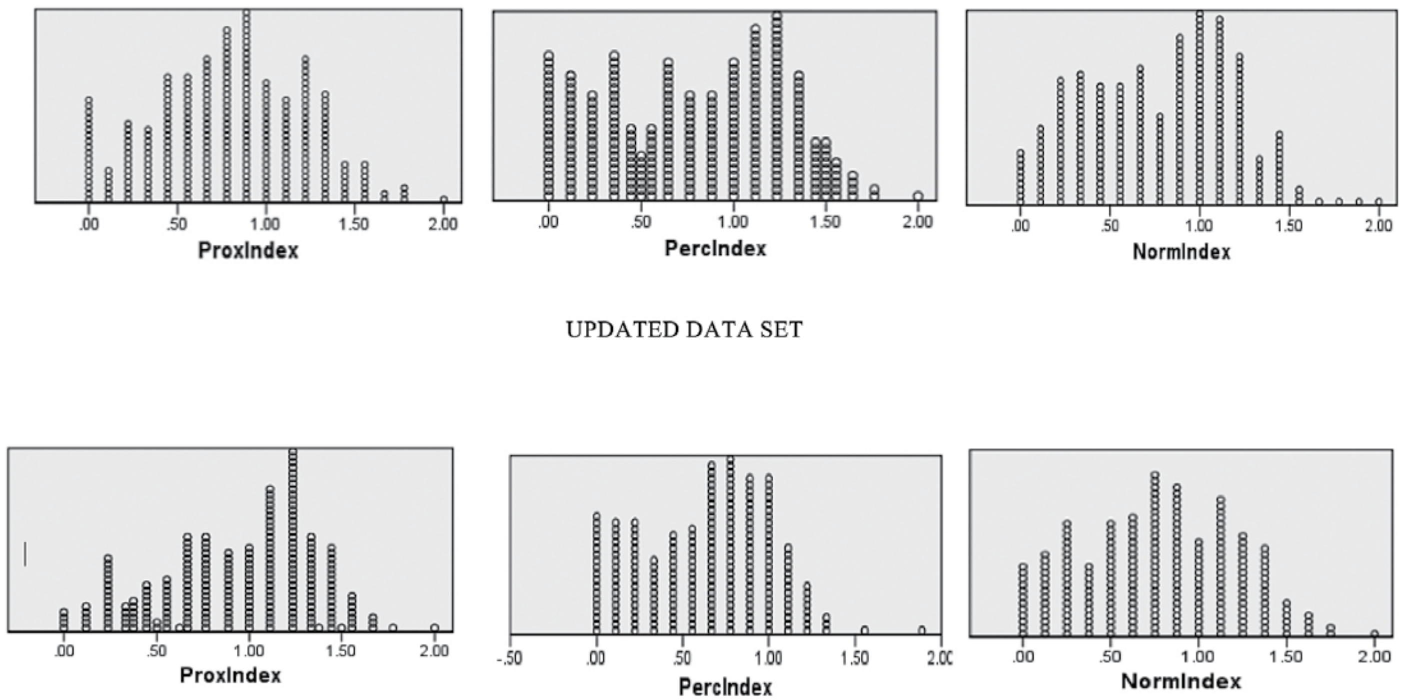
Examining the individual proximity index scores for each predictor in the original data set, the proximity index scores were more likely to classify a comparison institution as a peer than an almost-peer (65.6%), although the number of peers and almost-peers were the same. This is seen in Table 2.

The updated data set was similar in that 60.1% of the proximity index scores categorized a comparison institution as a peer although peers make up only two-fifths (42.3%) of both sets (11 vs. 15, respectively).

Percentile selection index

For the original data set, the percentile selection index range used to determine the peer institutions and almost-peer institutions was the same as the proximity selection index for the updated data set (PercI Range = 1.44 to 1.78) but more compressed than the percentile selection index for the updated data set (PercI Range = 1.11 to 1.56). For comparative purposes, the same cutoffs used for the proximity selection index were also applied to the percentile selection index, 95th percentile or higher for peers and

Figure 2. Selection Index Distributions



between the 90th and 95th percentiles for almost-peers.

As seen in Table 2, the original data set, the percentile selection index methodology had a more equitable split between the two peer groups with almost 54% (53.8%) of the percentile index scores classifying comparison institution as peers. However, the peer set is more than twice the size of the almost-peer set (21 vs. 9, respectively) and, therefore, the percentile index scores do not follow the individual percentile index score classification proportions. For the updated data set, about one-third (35.5%) of the percentile index scores categorized a comparison institution as an almost-peer, but the number of percentile selection index peers and almost-peers is similar (12 vs. 14, respectively).

Normative selection index

For the original data set, the normative selection index range (NormI = 1.22 to 1.89) was larger than the other selection indices. Therefore, the range for the updated data set was more compressed (NormI = 1.38 to 1.75) than the range for the normative selection index in the original data set. Again, the same cutoffs used for the other two selection indices were also applied to the normative selection index: 95th percentile or higher and between the 90th and 95th percentiles for peers and almost-peers, respectively.

In the original data set, the proportion of individual normative index scores that classified a comparison institution as a peer (60.7%) is the inverse of the actual proportion of peers (36.7%) to almost-peers. For the updated data set, the proportion of index scores that classified a comparison institution as a peer (60.2%) is more analogous to the actual proportion of peers and almost-peers, with more than half (55.6%) of the institutions at or above the 95th percentile.

Selection index distributions

An examination of each selection index distribution is shown in Figure 2. As seen, the distributions are shaped differently from what was expected. For example, in the original data set the proximity selection index should be very susceptible to outliers, but in fact it was more normally distributed than the percentile selection index that had a more pronounced right skewness. The probabilities associated with the percentile selection index were moderately uniform, yet

Table 3. Skewness and Kurtosis for the Predictors and Each Selection Index

Selection Index	Skewness	Kurtosis
Original Data Set		
25th Percentile Mathematics SAT	.56	–.15
Percent of Students Receiving Federal Grant Aid	.83	.28
Average Faculty Salary	.74	.99
FTE	.95	.72
Total Price of Attendance	–.01	–.22
Instructional Expenses Per FTE	1.79	4.10
Alumni Giving Rate	.70	.37
Proximity Selection Index	.00	–.51
Percentile Selection Index	–.03	–1.12
Normative Selection Index	.02	–.69
Updated Data Set		
Applicants per FTE	.80	.50
75th Percentile Mathematics SAT	–1.44	–.33
Percent of Faculty with Terminal Degree	–1.44	1.97
Average Faculty Salary	.54	.38
FTE	1.08	1.26
12-Month Enrollment Per FTE	4.01	21.06
Total Price of Attendance	–.11	–.79
Alumni Giving Rate	–.82	.63
Proximity Selection Index	–.31	–.71
Percentile Selection Index	–.01	–.57
Normative Selection Index	.06	–.71

multimodal or with more than one peak. For the updated data set, the proximity selection index distribution was more left skewed than both the percentile and normative selection index distributions and all distributions generated by the original data set.

All but the normative selection index distribution is misshapen. Again, the percentile index distribution appears to be multimodal.

To further investigate these incongruities, the skewness and kurtosis for each selection index were also computed. Results are shown in Table 3. In brief, the differences in asymmetry of the selection index distributions affect peer selection.

Paradoxically, only the proximity selection index distribution for the original data set was not left skewed. This is shown in Table 3 and Figure 2. Although slight, the percentile selection index was the most skewed (SE = –.03) of the original data set selection indices. For the updated data set, the proximity selection index posted the largest skew (SE = –.31) and the percentile selection index had the smallest skew (SE = –.01). Overall, the distributions gleaned from the updated data set seem to be more normally shaped than the original data set distributions.

Delving deeper into the data, it was discovered that the predictors used in the selection indices were also skewed. Skewness and kurtosis for the continuously scaled predictors are also shown in Table 3. Except for the Total Price of Attendance (SE = –.01) predictor, all were positively or right skewed in the original data set. The Instructional Expenses Per FTE predictor was the most skewed (SE = 1.79). For the updated data set, one-half (4) of the predictors were left skewed and one-half were right skewed. The 12-Month Enrollment Per FTE predictor (SE = 4.01) was the most skewed. Yet, even with the more pronounced skewness of the predictors in the updated data set compared to the original data set, the equitable proportion of left skew to right skew predictor distributions in the updated data set seemed to balance all the selection index distributions.

Examining the selection index distributions' kurtosis can also be informative. As seen in Table 3, all the selection index distributions for both the original and updated data sets had negative kurtoses. Negative kurtosis is associated with distributions with a flatter distribution compared to a normal distribution. A normal distribution would have a kurtosis of zero (DeCarlo, 1997). Not surprisingly, the percentile selection indices had the most negative kurtosis, indicating that it is less peaked than the other distributions. This is decipherable in Figure 2. In this regard, the selection index is working as intended. On the other hand, for the updated data set the kurtosis was similar across selection indices. The percentile selection index was the most peaked, albeit negative.

Table 4. Peer Overlap Across Peer Selection Indices

Selection Index/ices	Percent Overlap	
	Peer	Almost-Peer
Original Data Set		
Proximity/ Percentile	21.4%	4.3%
Proximity/ Normative	33.3%	21.3%
Percentile/ Normative	23.8%	6.4%
All 3	19.1%	2.1%
Updated Data Set		
Proximity/ Percentile	5.9%	12.0%
Proximity/ Normative	2.9%	20.0%
Percentile/ Normative	5.9%	4.0%
All 3	0.0%	0.0%

Selection index combinations

Comparison institutions were seldom chosen for membership in more than one selection index peer group. This is shown in Table 4. The original data set peer groups have the most overlap with one-third (33.3%) of the comparison institutions either a proximity or normative selection index peer.. This might be because the distribution for the proximity peer selection index is normally shaped and, therefore, the percentile and normative peer selection index transformations did not make much of a difference. For the updated data set, no comparison institution was a member of all three peer selection indices and only four comparison institutions (5.9% each for proximity/ percentile and percentile/ normative peer selection index combinations) were chosen for two peer selection index groups. Again, the peer selection index distributions—or, more precisely, the differences among the distributions—could have contributed to the uniqueness of each peer selection index membership. The proximity selection index is left skewed, the percentile selection index is multimodal, and the normative selection index is the most symmetric but slightly right skewed. Note that, unlike the original data set, overlap among peers was more prevalent for the three almost-peer selection index groups compared to the peer selection index groups.

Feasibly, symmetry could be achieved by combining selection indices, as was the case for the updated data set. Comparison institutions that were (a) only a normative selection index peer (NORMATIVE ONLY), (b) both a percentile and a normative selection index peer (BOTH), or (c) neither a percentile nor a normal selection index peer (NEITHER), were further investigated. As a starting point, the difference or distance between the average of each of these selection index peer sets and the target institution were examined for each continuously scaled predictor. This is seen in Figure 3. For the original data set, target institution was closest to the means derived from BOTH institutions for almost half (42.9%) of the seven predictors. For the updated data set,

Figure 3. Target Institution Comparisons to the Normative Selection Index Peers Only, Both Normative and Percentile Selection Index Peers, and Neither a Normative or Percentile Selection Index Peer

	Original Data Set		
	NORMATIVE	**BOTH**	**NEITHER**
25th Percentile Mathematics SAT	X		
Total Price of Attendance		X	
Average Faculty Salary		X	
FTE		X	
Total Price of Attendance	X		
Instructional Expenses Per FTE			X
Alumni Giving Rate			X
COUNT	2	3	2
	Updated Data Set		
	NORMATIVE	**BOTH**	**NEITHER**
Applicants/ FTE	X		
75th Percentile Mathematics SAT		X	
Percent Faculty with Terminal Degree	X		
Average Full-time Faculty Salary		X	
FTE	X		
12 Month Enrollment/ FTE		X	
Total Price of Attendance		X	
Alumni Giving Rate		X	
COUNT	3	5	0
	Both Data Sets		
	NORMATIVE	**BOTH**	**NEITHER**
TOTAL	*5*	*8*	*2*
PERCENT	*33.3%*	*53.3%*	*13.3%*

NORMATIVE: Normative Selection Index Peers Only
BOTH: Peers that are both Percentile and Normative Selection Index Peers
NEITHER: Peers that are neither Percentile nor Normative Selection Index Peers

BOTH institutions posted predictor means closest to the target institution for over half (62.5%) of the eight predictors. Combined across data sets, the target institution was closer to the institutions that were BOTH peers more frequently (53.3%) than the other two groups. Next was the NORMATIVE ONLY institutions, with one-third (33.3%) of the predictor means being nearest to the target institution compared to the other two groups. The NEITHER peer institutions fared the worst, with the distance between the target institution and the peer institution being the closest for only two predictors (13.3%) across data sets. In sum, institutions that are both percentile and normative selection index institutions tended to be the nearest to the target institution compared to the normative selection index–only institutions or those institutions that were in neither the percentile nor normative selection index peer groups.

A closer examination of the target institution's position on each continuously scaled predictor's distribution corroborates these findings. In Figure 3 green indicates the position of the target institution at the high end (right) of that predictor's distribution, yellow indicates the target institution in the middle of the predictor's distribution, and red indicates the target institution at the low end (left) of the distribution. As seen, there was no clear pattern. That is, the target institution's position on the distribution did not seem to influence peer selection index membership. This might be good news, in that the selection indices were somewhat unaffected by the target institution performance compared to other institutions.

CONCLUSION

This study investigated the use of three peer selection indices: proximity, percentile, and normative. These selection indices were applied to a predetermined set of institutions using institutional characteristics based on constituent feedback and institutional priorities. To select a set of peers that was well-informed and aligned with those priorities, the following steps were executed: (a) determination of what data to use, (b) data element standardization, (c) regression modeling to identify the predictors that were best correlated with key institutional attributes, (d) computation of index scores and corresponding selection indices, and (e) ascertaining the appropriateness of the selection indices. The last step was accomplished by comparing peer sets that were identified for each selection index to each other as well as considering the impact of the distributions of the predictors that make up each selection index.

As mentioned, the crux of the paper was to describe each selection index and to explore the differences among the three selection indices' peers. This research is innovative in that this was the first time that two of the selection indices, percentile and normative, were formally introduced and investigated. Moreover, the three selection indices were investigated simultaneously. As with our previous research, no selection index is endorsed outright but rather the plausibility and limitations of each was discussed. That said, selection index methodology holds promise as a robust and legitimate peer selection tool.

Because of the number of institutions in the initial data sets (N = 285 and N = 232 for the original and updated data sets, respectively), the 95th percentile of the selection index was established as the cutoff for choosing peers. Another set of almost-peers was also identified from institutions that were between the 90th and 95th percentiles. The two-tiered system to classify the immediacy of the institutions to the target institution is practical because of the relatively small range of index scores for all three selection indices. In turn, there might not be any meaningful differences regarding nearness to the target institution between institutions in the 90th to 95th percentile range and those in the 95th percentile to maximum range.

The results are not conclusive, but nonetheless indicate that using selection index composites—in particular a combination of the percentile and normative selection indices—can be useful. Although not a factor for the data sets used in this research, being mindful of the target institution's distribution position could be important and warrants further investigation.

Comparisons between the original data set and the updated data set reinforce the importance of regularly verifying an institution's list of peers. The peer institutions that were chosen changed over time, regardless of the selection index used. In fact, less than one-half (44.7%) of the proximity selection index peers or almost-peers identified in the updated data set were part of the original data set of proximity selection index peer or almost-peer list. The percentile selection index was somewhat less stable across data sets. Only one-third (33.3%) of the original data set percentile selection index peer or almost-peer institutions made the updated data set percentile selection index peer or almost-peer list. Likewise, only one-third (33.3%) of the normative selection index peer or almost-peers in the original data set were also peers in the updated data set. That said, the original data set of normative selection index almost-peers was very large compared to the other normative selection index peer sets, essentially ensuring some correspondence.

Admittedly, the Carnegie Classifications were modified between the extraction of the original and updated data sets and those modifications affected the selection of the initial set of peers and, ultimately, the final selection of peers. It is expected that Carnegie Classification will be updated more frequently and, therefore, the time of extraction of the two data sets used in this study was apropos. The results of this study can be taken as a warning that peer lists can become outdated and unsuitable. As this research demonstrates, it is reasonable to expect that institution characteristics and priorities change over time.

Finally, peer list differences among the selection indices demonstrate the importance of due diligence before, during, and arguably even after the selection process. Feedback from faculty and staff are key to this thoroughness. Beforehand, engaging constituent input not only helps to identify institutional priorities but, afterward, also reinforces their importance. Additionally, participation of constituents increases acceptance and use of the chosen set of peers.

Examining the set of institutions gleaned by each selection index affords both a comparison of the appropriateness of each institution as a peer and the set of institutions as a reasonable peer group (D'Allegro & Zhou, 2013). To that end, the choice of initial set of institutions is crucial. These institutions should be approximate to the target institution by proxy of both institutional characteristics and the predictors that will ultimately be used to choose a set of peers.

RECOMMENDATIONS

This study validates that peer selection based on a multistaged approach is necessary but not sufficient. Careful vetting of the appropriateness of the actual statistical steps and methodology are needed. As an example, several OLS regression models were generated to determine the best predictors of institutional quality, the mainstay of the target's priorities. However, other methodologies could be employed, including discriminant analysis, factor analysis, and variable match (Anderes, 1999).

Preliminary scrutiny of the variables to choose peers should be undertaken. To ensure the best mix of institutional characteristics to choose peers, this research engaged a two-stage regression modeling process. In the first stage, the best predictors were chosen from five different institutional characteristic categories. The second stage confirmed the correlation of the predictors to three institutional quality measures. Additionally, the location of the target institution on each potential predictor distribution and other anomalies should be identified and considered a priori to the actual determination of peers.

The examination of the selection indices is also in order. As the comparison of the distributions for each selection index revealed, resulting non-normal distributions had a profound impact on the selection of peers.

Both the type of institution as well as the purpose of the peer selection are key in determining the most appropriate information to collect (Shin, 2009). The use of historical information and data trends are posited as options but might not be fitting. As was the case in this study, historical information gleaned a different set of peers than more-current data.

Following the logic of the use of a two-tier taxonomy, two sets of peers were identified: peers and almost-peers. This affords the flexibility of choosing peers for different purposes and audiences. In addition, it somewhat mutes the imperfections of the peer selection methodologies.

The purpose of the study was to provide reasonable peer selection options. As stated, peer comparisons have many applications, such as determining quality, benchmarking salaries, evaluating programs, informing policy, and setting strategic direction. Coupled with the wide variety of institutional types and missions and the inconclusiveness of the results, no single selection index can be upheld to be better than the other selection indices. Accordingly, care should be taken to determine the best selection index or combination of selection indices. As for the latter, selection index combinations should be further investigated. A set of institutions determined to be a peer by two or more selection indices might prove to be more trustworthy and steadfast than the selection of peers from only one selection index. This seemed to be the case in this study, in which there was less distance from the target institution for most of the predictors for the combined selection index peers compared to the normative selection index–only peers, or, for comparison, institutions not selected by either the percentile or normative selection indices.

As of this study, there are few publications on peer selection methodologies. Evidence that is more conclusive is needed about peer selection models and the effect that target institution type might have on those models. As mentioned, the impact of peer comparisons on institutional quality and improvement has not been studied. Evaluation that invokes the use of peers seems to be in vogue but the question remains: Are peer comparisons or benchmarking superior to other types of comparative assessments or non-comparative evaluation? Further research should be able to address.

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Appendix A. Data Elements Used for Peer and Aspirant Selection: Time Frame, Indicator Type, and Source

Variable	Time Frame	Indicator Type	Indicator Source
Admit Yield	2011–2012, 2014–2015	Admissions	IPEDS
Number of Applicants, Total	2011–2012, 2014–2015	Admissions	IPEDS
Percent of Applicants Admitted	2011–2012, 2014–2015	Admissions	IPEDS
SAT Critical Reading 25th Percentile Score	2010–2011, 2014–2015	Admissions	IPEDS
SAT Critical Reading 75th Percentile Score	2010–2011, 2014–2015	Admissions	IPEDS
SAT Math 25th Percentile Score	2010–2011, 2014–2015	Admissions	IPEDS
SAT Math 75th Percentile Score	2010–2011, 2014–2015	Admissions	IPEDS
Percent of Full-Time Undergraduates Receiving Federal Grant Aid	2010–2011, 2013–2014	Admissions	IPEDS
Average Salary Equated to 9-Month Contracts of Full-Time Instructional Staff: All Ranks	2011–2012, 2014–2015	Faculty	IPEDS
Full-Time Primary Instruction Head Count	Fall 2011, Fall 2015	Faculty	IPEDS
Part-Time Primary Instruction Head Count	Fall 2011, Fall 2015	Faculty	IPEDS
Percentage of Faculty Holding Terminal Degrees	2011–2012, 2015–2016	Faculty	U.S. News & World Report
Estimated Fall Enrollment	Fall 2010, Fall 2015	Enrollment	IPEDS
Full-Time Equivalent (FTE)	Fall 2010, Fall 2015	Enrollment	IPEDS
Total Enrollment, Unduplicated	2010–2011, 2014–2015	Enrollment	IPEDS
Percentage of Classes Enrolling Fewer Than 20 Students	2011–2012, 2015–2016	Enrollment	U.S. News & World Report
Carnegie Classification: Basic (Arts & Sciences or Diverse Fields)	2010, 2015	Institutional Characteristic	IPEDS
Carnegie Classification: Enrollment Size & Setting	2010, 2015	Institutional Characteristic	IPEDS
Carnegie Classification: Undergraduate Profile (Transfer & Full-Time Proportions)	2010, 2015	Institutional Characteristic	IPEDS
Geographic Region	2011–2012, 2014–2015	Institutional Characteristic	IPEDS
Religious Affiliation	2011–2012, 2014–2015	Institutional Characteristic	IPEDS
Endowment (FASB)	2009–2010, 2013–2014	Financial	IPEDS
Instructional Expenses Per FTE (FASB)	2009–2010, 2013–2014	Financial	IPEDS
Tuition Total Price for In-District Students Living on Campus	2011–2012, 2014–2015	Financial	IPEDS
Alumni Giving Rate	2011–2012, 2015–2016	Financial	U.S. News & World Report
Bachelor's Degrees Conferred	2010–2011, 2014–2015	Student Success	IPEDS
Graduation Rates, Total Cohort (6 Years)	As of Aug. 31, 2010, As of Aug. 31, 2014	Student Success	IPEDS
Retention Rates, Total Cohort (1 Year)	Fall 2010, Fall 2014	Student Success	IPEDS

Appendix B. Equations Used to Compute Each Selection Index

PROXIMITY SELECTION INDEX EQUATIONS

ProxSvar1= (TIvarx – CIvarx)/ SDvarx

varx ϵ{1,…x}

ProxInstitution= average (ProxSvar1…ProxSvarx)

institution ϵ{1,…n}

Where:

ProxS = Proximity Score
ProxI = Proximity Selection Index
TI= Target Institution
CI= Comparison Institution
Var1-Varx= Predictors

0 assigned to ProxS when: $\text{ProxS} < -1$ or $\text{ProxS} > 1$
1 assigned to ProxS when: $-1 < \text{ProxS} < -.5$ or $.5 < \text{ProxS} < 1$
2 assigned to ProxS when: $-.5 < \text{ProxS} < .5$

PERCENTILE SELECTION INDEX EQUATIONS

PercSvar1= (TIvarx – CIvarx)

varx ϵ{1,…x}

PercInstitution= average (PercSvar1…PercSvarx)

institution ϵ{1,…n}

Where:

PercS = Percentile Score
PercI = Percentile Selection Index
TI= Target Institution
CI= Comparison Institution
Var1-Varx= Predictors

0 assigned to PercS when: $\text{PercS} < -.25$ or $\text{PercS} > .25$
1 assigned to PercS when: $-.25 < \text{PercS} < -.125$ or $.125 < \text{PercS} < .25$
2 assigned to PercS when: $-.125 < \text{PercS} < .125$

NORMATIVE SELECTION INDEX EQUATIONS

NormSvar1= (TIvarx – CIvarx)

varx ϵ{1,…x}

NormInstitution= average (NormSvar1…NormSvarx)

institution ϵ{1,…n}

Where:

NormS = Normative Score
NormI = Normative Selection Index
TI= Target Institution
CI= Comparison Institution
Var1-Varx= Predictors

0 assigned to NormS when: $\text{NormS} < -.25$ or $\text{NormS} > .25$
1 assigned to NormS when: $-.25 < \text{NormS} < -.125$ or $.125 < \text{NormS} < .25$
2 assigned to NormS when: $-.125 < \text{NormS} < .125$

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Appendix C. Examples on How to Calculate Each Selection Index

PROXIMITY SELECTION INDEX

Proximity Index

Notation Var_x	Predictors	Target Institution Value	Comparison Institution Value	Standard Deviation	$ProxS=(TI_{varx} - CI_{varx})/ SD_{varx}$			
					Equation	Result (Prox S)	Assigned*	
Var_1	FTE	1,810	1,400	200	(1,810-1,400)/200	2.05	0	Because ProxS > 1
Var_2	Average Faculty Salary	$ 45,000	$ 50,000	$ 15,000	(45,000-50,000)/15,000	0.33	2	Because ProxS> -.5 and ProxS < .5
Var_3	Total Cost of Attendance	$ 42,000	$ 37,500	$ 6,000	(42,000-37,500)/6,000	-0.75	1	Because ProxS > -.5 and ProxS < -1
					AVE of $ProxS_1$, $ProxS_2$, $ProxS_3$		1.00	

* 0 Assigned to ProxS when: ProxS < -1 or ProxS > 1
1 Assigned to ProxS when: -1< ProxS < -.5 or .5 < ProxS < 1
2 Assigned to ProxS when: -.5 < ProxS < .5

PERCENTILE SELECTION INDEX

Percentile Index

Notation Var_x	Predictors	Target Institution Value	Comparison Institution Value
Var_1	FTE	1,810	1400
Var_2	Average Faculty Salary	$ 45,000	$ 50,000
Var_3	Total Cost of Attendance	$ 42,000	$ 37,500

Notation Var_x	Predictors	Target Institution Value	Comparison Institution Value	$PercS=(TI_{varx} - CI_{varx})$			
				Equation	Result (PercS)	Assigned*	
Var_1	FTE	55.00%	40.00%	.55-.40	0.15	1	Because PercS > .125 and PercC < .25
Var_2	Average Faculty Salary	50.00%	62.00%	.50-.62	-0.12	2	Because PercS> -.125 and PercS < .125
Var_3	Total Cost of Attendance	62.00%	32.00%	.62-.32	0.30	0	Because PercS > .25
				Ave of $PercS_1$, $PercS_2$, $PercS_3$		1.00	

* 0 Assigned to PercS when: PercS < -.25 or PercS > .25
1 Assigned to PercS when: -.25< PercS < -.125 or .125 < PercS < .25
2 Assigned to PercS when: -.125 < PercS < .125

Appendix C. Examples on How to Calculate Each Selection Index

NORMATIVE SELECTION INDEX

Normative Index	Notation Var_x	Predictors	Target Institution Value	Comparison Institution Value				
	Var_1	FTE	1,810	1,400				
	Var_2	Average Faculty Salary	$ 45,000	$ 50,000				
	Var_3	Total Cost of Attendance	$ 42,000	$ 37,500				
	Converted to the Area Corresponding to the Standardized Normal Scores*							
					$NormS=(TI_{varx} – CI_{varx})$			
	Notation Var_x	**Predictors**	**Target Institution Value**	**Comparison Institution Value**	**Equation**	**Result**	**Assigned****	
	Var_1	FTE	0.35	0.45	.35-.45	-0.10	2	Because NormS > -.125 and NormS < .125
	Var_2	Average Faculty Salary	0.75	0.88	.75-.88	-0.13	1	Because NormS > -.25 and NormS < -.125
	Var_3	Total Cost of Attendance	0.88	0.48	.88-.48	0.40	0	Because NormS > .25
					Ave of $NormS_1$, $NormS_2$, $NormS_3$		1.00	

* To compute the area:

1. Calculate the z-score= $(Value_{Varx} - Mean_{Varx})/StdDev_{Varx}$
2. Find the area under the curve to the right of the z-score (NORM.S.INV function in Excel)

** 0 Assigned to NormS when: NormS < -.25 or NormS > .25
1 Assigned to NormS when: -.25< NormS < -.125 or .125 < NormS < .25
2 Assigned to NormS when: -.125 < NormS < .125

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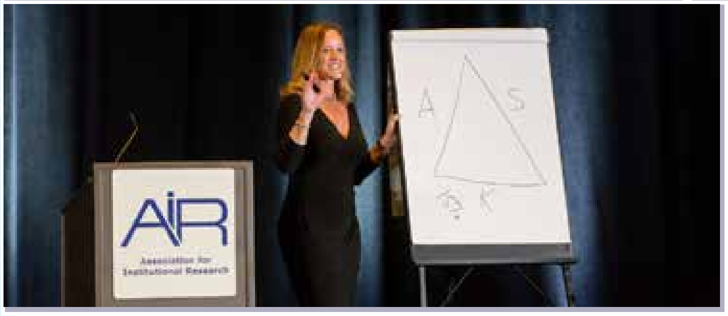

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