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Measuring X-Efficiency in NCAA Division III Athletics

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Abstract

This article expands on previous research regarding the relative efficiency of National Collegiate Athletic Association III Athletic Departments. In our analysis, we employ Frontier Analysis to develop an efficiency score for each program over the time frame of 2007-2008 to 2011-2012. We find that private schools dominate the rankings of the most efficient athletic departments. In addition, it is clear that some inputs are more valuable than others. In reviewing the yearly cross-sectional results, it is evident that for the average institution, increasing the number of female students participating in sports will yield the greatest expected increases in Director's Cup points.

Keywords

X-efficiency, NCAA Division III, efficiency, sports, athletic departments

In light of the success of Michael Lewis's book, *Moneyball*, the idea of integrating mathematics with sports efficiency has captured researcher's attention. The concept of X-efficiency, historically used in the analysis of bank operations, has been expanded to the sports world and serves as a methodology to analyze efficiency. Prior sports efficiency research has focused primarily on individual sports with high revenue streams, such as the National Football League (e.g., Hadley, Poitras, Ruggiero, & Knowles, 2000), Major League Baseball (e.g., Horowitz, 1994a,

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1994b; Porter & Scully, 1982), and Major League Soccer (Haas, 2003). Efficiency analysis provides these sports a benchmark to gauge performances and input–output relationships.

Although an extensive portfolio of empirical analyses in the sports economics literature exists, there has yet to be significant research into National Collegiate Athletic Association (NCAA) Division III athletics. However, NCAA III has the input characteristics of large organizations and the output goals. The recognition of this research avenue allows for the use of an X-efficiency technique and the analysis of a previously unexplored enterprise.

X-efficiency research requires the selection of an output measure. In the case of NCAA III athletics, the Director's Cup Score measures a university's output. This article employs data on this score and various input measures from the 2007-2008 to the 2011-2012 academic year (beginning July 1).[1] This score serves as the dependent variable in various regressions used to estimate X-efficiency. Note that the regressions are similar to those reported by Jones (2012) for Division I athletics, with the important exception that X-efficiency analysis, as used in the research cited earlier, drops the assumption that all schools utilize resources efficiently.

As a result of this study, universities may be assisted in a number of ways. Critical factors are identified that could potentially assist and direct university officials to areas of concentration. Universities may find other, more successful, counterparts, which they could imitate to improve their existing athletic programs. Also, comparisons may be drawn between competing schools in their respective conferences or states.

Literature Review

The literature review serves as a template to identify proper inputs and outputs that create the functional model. Past academic papers, which use X-efficiency analysis, have created a menu of potential inputs. Inputs are assets injected into a system with the ability to turn said inputs into outputs. This article turns to the research on efficiencies in university departments to clarify our input selection.

Afonso and Santos (2005) develop their model by identifying the most common inputs in the existing literature to maximize university department's efforts. Inputs include staff numbers, nonstaff numbers, percentage of faculty with a PhD, total expenditures, and expenditures for academic staff and other expenditures. Common output variables consist of graduation rate, freshmen retention rate, student numbers (both graduate and undergraduate), total number of certificates conferred, and research publications and citations. Personnel, operating expenses and space are applied as inputs in Tauer, Fried, and Fry (2007), Kaoa and Hung (2006), and Belfield (2012). Daghbashyan (2013) expands the potential input menu by introducing funding through government or external entities. Abbott and Doucouliagosa (2001) deviate from the early literature by using the total number of academic staff (full-time equivalent [FTE]), number of nonacademic staff (FTE), expenditure on all other inputs other than labor, and value of noncurrent assets. Afonso and Santos (2005) also include average total spending per student, teachers to students ratio in public universities, and FTE rate as their inputs.

X-efficiency models have been applied to specific sports as opposed to athletic departments. Performance measures of offensive and defensive production such as average yards per rush, percentage of passes intercepted, and so on are applied to the National Football League (Hadley et al., 2000). Haas (2003) also includes coach and player wages as inputs while team points earned, average attendance, and total revenue are used as outputs in his X-efficiency analysis of Major League Soccer. Einolf (2004) assesses Major League Baseball by using player salaries as inputs while using team wins, team batting average, and team earned run average as outputs.

Athletic departments attempt to maximize the output produced by a given set of inputs. X-efficiency uses the mix of inputs and their relationship with the output to indicate how successful the institution is in achieving efficiency. For simplicity, this article presumes that the Director's Cup Score is the sole output of the institution. Of course, universities have a variety of goals but only athletic performance is measured here.

Data and Descriptive Statistics

For this study, data are drawn from two sources. The Office of Postsecondary Education of the U.S. Department of Education publishes annual information for schools participating in an organized division. The department created the Equity in Athletics Data Analysis Cutting Tool, which provides relatively complete data, measuring yearly inputs for each institution (U.S. Department of Education, 2013).

The Cutting Tool provides detailed information pertaining to the way universities allocate their recourses within their athletic departments. This data set provides information such as operating expenses to the number of coaches per athletic sport. Basic information is also included such as institution size and classification as public or private. Extracted data from this set will make up the inputs employed in this analysis. To establish the output, we use the database created by the National Association of Collegiate Directors of Athletics' standings for the Learfield Sports Director's Cup (National Association of Collegiate Directors of Athletics, 2013). The Director's Cup score is based on the rank an athletic department places within the NCAA for an athletic season. For example, if a school records a first place finish in Women's Cross Country, it is awarded 100 points. A second place finish receives fewer points. It is the total of all points from 20 sports, split equally between men's and women's teams, which constitute the Director's Cup score.

The dependent and independent variables are described in Table 1. All figures are annual averages for a balanced panel ranging across academic years 2008 through

Table 1. Descriptives.

Variable	Mean	Std. Dev.
Points	228.94	198.12
Men participants	287.95	99.8
Women participants	194.2	70.93
Operating expenses	US$6.33E+06	US$4.24E+06
Small school (<2000)	0.427	0.495
Large school (>6000)	0.122	0.327
Private school	0.792	0.406

Note. Std. Dev. = standard deviation; N = 1,060.

2012, with observations covering a period starting July 1 of the prior year and running through June 30 of any specific year. Although the first four variables listed are analyzed in natural logs (see subsequently), their mean absolute values are provided in Table 1, with operating expenses adjusted to real 2010 dollars using the CPI-U deflator (U.S. Department of Labor, 2013). Notable patterns include around 50% more men than women participating in athletics, operating expenses average above US$6 million per year, schools tend to be small, and almost 80% of the institutions are private.

The Director's Cup score is dictated by the place each school finishes annually in each sport, both men's and women's. At the conclusion of the athletic year, each university's final sport totals are aggregated arriving at the final total for the Cup. It is important to keep in mind that all sports are weighted equally. This is notable since an analysis of other NCAA Divisions (i.e., I or II) might require weighting due to the importance of revenue-generating sports (such as men's football and basketball). The Director's Cup score, and this research, places equal weight on each individual sport.

Method

A Stochastic Frontier (SF) analysis estimates the equation:

$$DC_{it} = f(x_{it}, z_{it}) + v_{it} - u_{it}, \text{where } i = 1, \ldots, N; t = 1, \ldots, T, u_{it} \geq 0, \quad (1)$$

where DC represents the output (Director's Points) of institution i in time period t, f is a production function linking the output to inputs x, with labor input represented by the number of men and (separately) the number of women participating in athletics and capital input proxied by operating expenses. The output is related to environmental factors z, which includes dummy variables for small and large schools (by enrollment), and a dummy variable for private school status, while v is a stochastic error term and u is the measure of technical inefficiency, with a lower bound of zero for relatively efficient institutions. Initially, environmental factors are assumed to shift the production function independent of the inputs.

Collier, Johnson, and Ruggiero (2011) note that estimates of (1) for zero-sum measures of efficiency are biased and generate inaccurate rankings. However, total DC points are not fixed for the balanced panel used here because schools earning positive points in some years but not others are excluded so no correction for zero-sum bias is provided subsequently.

It is reasonable to assume that inputs are related to output via a Cobb-Douglas production function. If instead linear relationships are specified, it would be possible to engage in production with one input or another (e.g., labor or capital), which is implausible in most production settings, including intercollegiate athletics. The Cobb-Douglas specification assumes instead that inputs are complementary. As a practical matter, a linear regression with a natural logarithmic transformation of the outputs and inputs yields this specification.

The Cobb-Douglas specification yields input coefficients that permit estimation of returns to scale. If the sum is greater than unity, there are increasing returns to scale. A sum of unity denotes constant returns to scale, while values less than unity imply decreasing returns to scale. For the production function considered here, constant returns to scale is plausible, since an institution fielding 10 athletic teams could add or subtract one of those teams at random and would likely increase or reduce the number of student athletes, operating expenses, and DC points proportionately.[1]

The use of panel data raises the question of whether inefficiency is time invariant or time varying. At least in relatively short panels (e.g., $T < 10$), some inefficiency is likely time invariant. For example, if managerial culture is both causally related to efficiency and changes slowly (e.g., see Schein, 1996), then it is reasonable to specify inefficiency as time invariant. The random-effects maximum-likelihood model of Battese and Coelli (1988) is used to estimate purely time-invariant inefficiency. A more general maximum-likelihood specification by Kumbhakar (1990) is estimated to account for the possibility that inefficiency is quadratic in time, with nonzero coefficients on the quadratic signifying that the quadratic represents an improvement in the specification (a specification with a linear time trend, by Battese & Coelli, 1992, is less general so not reported here). A fixed-effects version of the time-invariant model with within-group least squares, due to Schmidt and Sickles (1984), is also estimated. In this model, organizational-level fixed effects on production are assumed, with the time-invariant inefficiency indicating the effects of changes in the inputs in terms of changes in output across the panel. The results of this model are somewhat suspect because the coefficient estimates are mainly driven by organizations that experience unusual growth or decline in input levels, and those organizations may not be representative of Division III athletics as a whole.

In traditional regression models, heteroskedasticity is of concern because the standard errors of the coefficients may be understated, leading to overstated inferences regarding significance. In response to this concern, bootstrap standard errors are estimated (with 50 iterations). However, in SF models, heteroskedasticity is more troubling because it can bias the inefficiency estimates and lead to misspecified rankings (Kumbhakar & Lovell, 2000). For example, if larger institutions vary more than smaller institutions in the way specific resources are utilized, heteroskedasticity may influence the results. The time-varying maximum likelihood dummy variables model of Battese and Coelli (1995) provides a correction for heteroskedasticity.

For each of the models described earlier, if there are omitted, time-invariant environmental variables, the presumption that at least some inefficiency is time invariant may mistakenly attribute environmental effects to inefficiency. Greene (2005a, 2005b) developed fixed- and random-effects models that assume on the contrary that any time-invariant heterogeneity across organizations is unrelated to inefficiency. The information requirements of these methods are severe, so it is not surprising that Belotti and Ilardi (2012) discovered that variance parameter (and inefficiency) estimates were inconsistent for relatively short panels (i.e., $T < 10$). For that reason, those estimates are not provided.

Some assumption is required regarding the distribution of u. The Battese and Coilli's (1988) model assumes a half-normal distribution as does the Kumbhakar's (1990) model. The fixed-effects model of Schmidt and Sickles (1984) makes no assumptions about the distribution, while the heteroskedasticity-corrected model of Battese and Coelli (1995) assumes u has a truncated-normal distribution.

As is standard, the measure of technical efficiency follows Jondrow, Lovell, Materov, and Schmidt (1982), such that, ignoring time variations, $\text{TechnicalEfficiency}_i = \exp(-u_i)$. In the model with time-varying inefficiency (Battese & Coelli, 1995), the term is averaged across all periods, or $\text{TechnicalEfficiency}_i = \{\sum \exp(-u_{it})\}/T$. The measure of technical efficiency is typically interpreted in terms of the proportion of outputs obtained relative to a perfectly efficient proportion of unity, although no particular institution needs to achieve a value of unity for the estimation.

Estimation uses Stata 12.1 and the SF panel commands written for Stata by Belotti, Daidon, Ilardi, and Atella (2012). The rankings are presented separately for private and public institutions. The rationale for doing so is that none of the public schools are flagship universities within their state.[2] That status places them at a competitive disadvantage in recruiting top athletes relative to both the flagship schools and the elite private schools, such as Amherst, Emory, or Williams.

Results

The first numeric column of Table 2 presents the random-effects results for the Battese and Coelli (1988) time-invariant estimator. A χ^2 test failed to reject the hypothesis of constant returns to scale or that the three input coefficients summed to unity ($\chi^2 = 0.04$, 1 *df*, $p < .844$). The input coefficients can be interpreted as partial elasticities such that, for example, a 10% increase in operating expenditures would

Table 2. Panel Frontier Analyses, 2008-2012.

Variables	Time-Invariant Inefficiency	Time-Varying Inefficiency
Men participants	0.36**	0.32*
	(0.13)	(0.14)
Women participants	0.53**	0.73**
	(0.14)	(0.17)
Operating expenses	0.14*	0.15
	(0.07)	(0.08)
Small	−0.18*	−0.20*
	(0.08)	(0.09)
Large	0.18	0.41**
	(0.22)	(0.15)
Private	0.03	0.11
	(0.15)	(0.15)
Constant	−0.51	−2.12*
	(1.13)	(0.94)
Het *v* constant		2.05**
		(0.32)
Observations	1,060	1,060
σ^2	.59	
γ	.62	
Wald's χ^2	93.27	269.97
Significance	0.00	0.00

Note. σ^2 and γ are not available for the time-varying model. Standard errors in parentheses.
$^{**}p < .01$, $^{*}p < .05$.

generate an expected 1.4% increase in DC points. The largest coefficient is for women participants at .53. This result is sensible, given that the mean number of women athletes is smaller than the number of men (see Table 1), while DC points reward men's and women's sports performance equally. The significant coefficient for small schools suggests that, on average, institutions with fewer than 2,000 students earn 18% fewer DC points, which is again a plausible finding.

The σ^2 and γ terms represent the standard deviation of the within- and between-school residuals, respectively. The values suggest that the residuals are of similar size. The Wald's χ^2 of 93.27 is significant and suggests a reasonable goodness of fit for the estimation.

Results for the Kumbhakar's (1990) model, permitting a time quadratic for the inefficiency term, were estimated. Tests for whether the relevant coefficients were significantly different from zero failed to reject the null for both the linear term ($\chi^2 = 0.00$, 1 *df*, $p < .998$) and the quadratic ($\chi^2 = 0.00$, 1 *df*, $p < .999$), so the results are not shown.

Results for the Schmidt and Sickles (1984) fixed-effects model yielded a test for constant returns to scale rejecting the null hypothesis that the input coefficients summed to unity ($\chi^2 = 8.69$, 1 *df*, $p < .003$); indeed, the coefficients summed to .42, suggesting strongly decreasing returns to scale. All but one of the individual coefficients were insignificant, and the coefficient that achieved significance at conventional levels suggests that large schools generate 62% fewer DC points, a result that strains credulity. Further, the overall fit of the regression was relatively poor (Wald $\chi^2 = 10.65$, $p < .06$). It is reasonable to conclude that there is insufficient variation in the inputs to yield meaningful results from the fixed-effects model so the results are not reported.

The time-varying maximum-likelihood dummy variables model of Battese and Coelli (1995) is estimated next to correct for heteroskedasticity. As an initial check, all three environmental variables were entered, as they might affect either the error or the inefficiency term. The coefficients for the environmental variables were uniformly insignificant. However, a significant coefficient was identified for the constant term, as it affects the error term so these results are shown in the right-hand column of Table 2. The heteroskedasticity coefficient for the error term (Het *v* constant) is significant, suggesting the correction is warranted. The results fail to reject constant returns to scale ($\chi^2 = 2.32$, 1 *df*, $p < .128$), and the pattern of input coefficients remains similar to that for the time-invariant results. The Wald χ^2 of 269.97 is significant and suggests a reasonable goodness of fit. We later report rankings using both sets of results presented in Table 2.

It is possible that the larger coefficient for women than for men as inputs into the athletic production process is a statistical artifact of the analysis not accounting for football. At Division I institutions, football, particularly among the elite Bowl Championship Series (BCS) championship schools, plays a pivotal role in the generation of revenues and athletic success (Jones, 2012). For the present analysis, it is possible that men's football helps to subsidize women's sports, generating an apparent efficiency advantage that does not exist, or institutions with men's football may attract better male and female athletes, or generate a larger fan base for other sports at the institution.

Regardless of the specific causal mechanism, if the absence of a football variable explains the relatively high coefficient on the number of women athletes, then including the variable should reduce the effect. Relevant results after adding a football dummy variable to the specifications reported in Table 2 are presented in Table 3. For the time-invariant model, constant returns to scale cannot be rejected ($\chi^2 = 0$, 1 *df*, $p < .95$), the football coefficient is insignificant, and the pattern of input coefficients remains unchanged. The time-varying model was tested for whether football was associated with heteroskedasticity in either the error or the inefficiency term and, finding insignificant coefficients, the results reported in the table exclude such terms. Again, constant returns to scale cannot be rejected ($\chi^2 = 2.99$, 1 *df*, $p < .084$), the football coefficient is insignificant, and the pattern of input coefficients remains as before. Therefore, the results cannot be attributed to the exclusion of football from the main analysis.

Table 3. Panel Frontier Analyses With Football, 2008-2012.

Variables	Time-Invariant Inefficiency	Time-Varying Inefficiency
Men Participants	0.34*	0.47*
	(0.16)	(0.19)
Women participants	0.53**	0.67**
	(0.13)	(0.14)
Operating expenses	0.14*	0.15*
	(0.07)	(0.07)
Small	−0.18*	−0.18*
	(0.08)	(0.09)
Large	0.18	0.43**
	(0.20)	(0.14)
Private	0.03	0.13
	(0.20)	(0.12)
Football	0.02	−0.13
	(0.15)	(0.16)
Constant	−0.42	−2.54**
	(0.98)	(0.98)
Het *v* constant		−2.07**
		(0.35)
Observations	1,060	1,060
σ^2 (σ *u*)	0.59	
γ (σ *v*)	0.62	
Wald χ^2	177.62	261.88
Significance	0.00	0.00

Note. Standard errors in parentheses.
$^{**}p < .01$, $^{*}p < .05$.

Efficiency Rankings

Efficiency estimates and annual average DC points for the 10 most efficient private and public schools are provided in Tables 4 and 5, respectively. Rankings using the time-invariant estimates are on the left, while those from the time-varying estimates are on the right. Regardless of the model used, the rankings are similar, with only two schools appearing in one private list but not the other, and three schools appearing on one public list but not the other. A complete list of the rankings confirms the stability of the estimates (see Appendix Table A1). The similarity is particularly impressive, given that one model presumes that inefficiency is constant over time, while the other does not and corrects for heteroskedasticity.

Perhaps surprisingly, the highest technical efficiency figures, for Calvin College, are just below .87. This figure implies that the most efficient institution in the sample could achieve an approximate 13% improvement in efficiency, holding inputs constant. Of greater importance, technical efficiency and average DC points are related but distinct, with the simple correlation between the two taking a value of .78 for the

Table 4. Ten Most Efficient Private Schools, 2008-2012.

Institution	Time-Invariant Model	Points	Institution	Time-Varying Model	Points
Calvin College	0.858	580.8	Calvin College	0.869	580.8
Amherst College	0.832	894.2	Amherst College	0.854	894.2
Emory University	0.831	712.85	Messiah College	0.830	580.05
Messiah College	0.776	580.05	Emory University	0.826	712.85
Williams College	0.762	607.5	Illinois Wesleyan Univ.	0.826	607.5
Washington Univ. in St Louis	0.756	914.95	Methodist University	0.830	367.5
Illinois Wesleyan Univ.	0.739	607.5	Wartburg College	0.819	602.35
Wartburg College	0.722	602.35	Williams College	0.814	1118.1
Methodist University	0.676	367.5	Cabrini College	0.803	224.2
Claremont McKenna College	0.657	455.7	Nebraska Wesleyan University	0.798	306.2

time-invariant and .65 for the time-varying estimates. This is a comforting finding in terms of the purpose of the model, which is not to identify DC points winners (which are readily available already) but instead to identify schools that use their resources efficiently, regardless of the level of those resources.

Conclusions

Whether private or public, the inputs allocated to success in NCAA III athletics are an important management tool. The issue of returns to this investment is present at a time when there is increased competition for students. All Colleges and Universities were found to suffer from X-inefficiency, but it is also clear that some inputs are more valuable than others.

Although the fixed-effects model did not yield meaningful results, both the time-invariant and the time-varying models likely suffer from omitted variable bias. This deficiency implies that some of the divergence in estimated efficiency is likely due to differences in unmeasured resources or technologies, which could be related to student attitudes, school reputation effects, location, or differences in physical plant.

In reviewing the results, and even after controlling for the existence of a men's football program, it is clear that for the average institution, increasing the number of female students participating in sports will yield the greatest expected increases in Director's Cup points. This result is sensible, given the relatively

Table 5. Ten Most Efficient Public Schools, 2008-2012.

Institution	Time-Invariant Model	Points	Institution	Time-Varying Model	Points
College of New Jersey	0.747	695.65	University of Texas at Tyler	0.818	281.6
University of Texas at Tyler	0.660	281.6	College of New Jersey	0.800	695.65
Salisbury University	0.606	556.45	Christopher Newport Univ.	0.794	457.25
Christopher Newport Univ.	0.593	457.25	Salisbury University	0.740	556.45
Univ.Wisconsin–Whitewater	0.583	729.95	Eastern Conn. State Univ.	0.731	209.7
Univ. Wisconsin–Oshkosh	0.573	584.9	Univ. Wisconsin–Oshkosh	0.714	584.9
Univ. Wisconsin–Stevens Point	0.570	629.95	Univ. Wisconsin–Stevens Point	0.703	629.95
SUNY College at Cortland	0.531	687.6	Univ. Wisconsin–Whitewater	0.703	729.95
Univ. Wisconsin–Eau Claire	0.511	636.67	Farmingdale	0.672	197.35
Univ. Wisconsin–La Crosse	0.481	572.9	Keene State College	0.671	269.2

Note. Univ. = university.

low levels of women's participation and the equal weighting of women's athletics in the points system. Although the analysis addressed technical and not allocative efficiency, given the inherent similarity of women and men as student athletes, it is reasonable to interpret the larger measured effect of women athletes on Director's Cup points as a result of allocative inefficiencies: Holding the total number of athletes constant, many institutions could replace some number of men athletes with an identical number of women athletes and increase their expected Director's Cup points. Regardless of this conclusion, it was also found that adding male athletes increases expected Director's Cup points, although with a smaller coefficient, the impact is less.

There are also exogenous effects related to size: relative to the medium-sized institutions (2,000 to 5,999 students), smaller schools generate fewer points, perhaps because they have a smaller pool of potential athletes to draw from, while larger schools have a significant advantage according to the time-varying model. Regardless of the inputs, the results suggest that each of the schools could improve their point standings with existing resources by improving efficiency.

Appendix

Table A1. Efficiency Rankings of All Private and Public D3 Institutions, 2008-2012.

Private Institutions	Rank Time-Invariant Model	Rank Time-Varying Model	Public Institutions	Rank Time-Invariant Model	Rank Time-Varying Model
Calvin College	1	1	The College of New Jersey	1	2
Amherst College	2	2	The University of Texas at Tyler	2	1
Emory University	3	5	Salisbury University	3	4
Messiah College	4	3	Christopher Newport University	4	3
Washington University in St Louis	5	12	University of Wisconsin-Whitewate	5	8
Williams College	6	8	University of Wisconsin-Oshkosh	6	6
Illinois Wesleyan University	7	4	University of Wisconsin-Stevens P	7	7
Wartburg College	8	7	SUNY College at Cortland	8	12
Methodist University	9	6	University of Wisconsin-Eau Clair	9	14
Claremont McKenna College	10	11	Eastern Connecticut State Univers	10	5
Cabrini College	11	9	University of Wisconsin-La Crosse	11	17
Nebraska Wesleyan University	12	10	Keene State College	12	11
Middlebury College	13	16	Montclair State University	13	18
Coe College	14	13	Farmingdale State College	14	9
Trinity University	15	14	University of Mary Washington	15	16
University of St Thomas	16	20	Rowan University	16	22
North Central College	17	19	Rhode Island College	17	13
Moravian College	18	17	University of California-Santa Cr	18	20
Whitworth University	19	21	SUNY College at Plattsburgh	19	15

(continued)

Table A1. (continued)

Private Institutions	Rank Time-Invariant Model	Rank Time-Varying Model	Public Institutions	Rank Time-Invariant Model	Rank Time-Varying Model
Webster University	20	15	United States Merchant Marine Aca	20	10
DePauw University	21	24	University of Wisconsin-Plattevil	21	21
Thomas More College	22	22	SUNY at Geneseo	22	19
Heidelberg University	23	18	Kean University	23	24
University of Redlands	24	26	CUNY Hunter College	24	27
Stevens Institute of Technology	25	27	CUNY College of Staten Island	25	26
Oglethorpe University	26	23	SUNY at Fredonia	26	23
Wheaton College (MA)	27	30	SUNY College at Oneonta	27	25
George Fox University	28	25	CUNY Bernard M Baruch College	28	29
Hope College	29	28	University of Wisconsin-River Fal	29	30
Kenyon College	30	32	Western Connecticut State Univers	30	28
Linfield College	31	31	University of Wisconsin-Stout	31	34
Denison University	32	34	Castleton State College	32	32
University of Chicago	33	33	Salem State University	33	31
Skidmore College	34	37	The Richard Stockton College of N	34	33
Bowdoin College	35	43	SUNY College at Buffalo	35	35
Transylvania University	36	36	Bridgewater State University	36	39
McMurry University	37	35	William Paterson University of Ne	37	41
Tufts University	38	51	SUNY College at Brockport	38	43
Carleton College	39	40	The University of Texas at Dallas	39	37
Kalamazoo College	40	29	Westfield State University	40	42
Gustavus Adolphus College	41	49	University of Southern Maine	41	40
Centre College	42	41	Ramapo College of New Jersey	42	36

(continued)

Table A1. (continued)

Private Institutions	Rank Time-Invariant Model	Rank Time-Varying Model	Public Institutions	Rank Time-Invariant Model	Rank Time-Varying Model
Eastern University	43	38	University of Massachusetts-Dartm	43	44
Washington and Lee University	44	45	Rutgers University-Camden	44	38
Brandeis University	45	39			
Pomona College	46	44			
Lynchburg College	47	47			
Carnegie Mellon University	48	46			
Massachusetts Institute of Techno	49	56			
Elizabethtown College	50	48			
University of La Verne	51	42			
Ohio Northern University	52	52			
Haverford College	53	55			
Saint Norbert College	54	50			
Wheaton College (ILL)	55	57			
Central College	56	60			
University of Mount Union	57	58			
Roanoke College	58	61			
Luther College	59	66			
Husson University	60	59			
Delaware Valley College	61	54			
Ohio Wesleyan University	62	63			
Carthage College	63	68			
Springfield College	64	77			
North Carolina Wesleyan College	65	53			
Wittenberg University	66	73			
Monmouth College	67	72			
Loras College	68	75			
Virginia Wesleyan College	69	71			
Olivet College	70	64			
University of Mary Hardin-Baylor	71	62			
St Lawrence University	72	87			

(continued)

Table A1. (continued)

Private Institutions	Rank Time-Invariant Model	Rank Time-Varying Model	Public Institutions	Rank Time-Invariant Model	Rank Time-Varying Model
New York University	73	109			
Chapman University	74	74			
Rose-Hulman Institute of Technolo	75	65			
Juniata College	76	80			
Dominican University	77	69			
Greenville College	78	70			
Illinois College	79	67			
Hobart William Smith Colleges	80	83			
Baldwin-Wallace College	81	79			
Elmira College	82	86			
Trinity College	83	97			
Southwestern University	84	76			
Whitman College	85	85			
Louisiana College	86	78			
Endicott College	87	91			
Medaille College	88	82			
Carroll University	89	96			
Greensboro College	90	84			
Dickinson College	91	101			
Wesley College	92	90			
Neumann University	93	98			
Buena Vista University	94	81			
Allegheny College	95	103			
Bates College	96	116			
DeSales University	97	93			
Keystone College	98	92			
Washington & Jefferson College	99	104			
Gettysburg College	100	110			
Bethel University	101	99			
Franklin and Marshall College	102	111			
Case Western Reserve University	103	102			
Wilkes University	104	94			
California Lutheran University	105	95			

(continued)

Table A1. (continued)

Private Institutions	Rank Time-Invariant Model	Rank Time-Varying Model	Public Institutions	Rank Time-Invariant Model	Rank Time-Varying Model
Maryville College	106	89			
Huntingdon College	107	100			
Lebanon Valley College	108	117			
Simpson College	109	106			
Hardin-Simmons University	110	105			
York College Pennsylvania	111	114			
Thiel College	112	88			
Western New England University	113	107			
Saint John Fisher College	114	108			
University of Rochester	115	113			
Colorado College	116	112			
Norwich University	117	119			
Cornell College	118	120			
Otterbein University	119	124			
Manchester College	120	122			
Colby College	121	132			
University of Dubuque	122	118			
Franklin College	123	115			
Hamilton College	124	125			
Augsburg College	125	123			
Vassar College	126	130			
University of Puget Sound	127	126			
St Olaf College	128	134			
Guilford College	129	121			
The College of Saint Scholastica	130	128			
Nazareth College	131	131			
Westminster College	132	139			
Augustana College	133	140			
Texas Lutheran University	134	129			
Elmhurst College	135	138			
King's College	136	133			
Aurora University	137	135			
Concordia College at Moorhead	138	151			
Muhlenberg College	139	141			

(continued)

Table A1. (continued)

Private Institutions	Rank Time-Invariant Model	Rank Time-Varying Model	Public Institutions	Rank Time-Invariant Model	Rank Time-Varying Model
Alvernia University	140	136			
Grinnell College	141	146			
Catholic University of America	142	149			
Capital University	143	137			
Occidental College	144	145			
Ursinus College	145	150			
Emmanuel College	146	147			
Connecticut College	147	155			
Willamette University	148	142			
University of Scranton	149	148			
Lakeland College	150	127			
Marymount University	151	143			
Adrian College	152	157			
Swarthmore College	153	153			
Wilmington College	154	144			
Washington College	155	152			
Lycoming College	156	156			
Union College	157	154			
University of New England	158	160			
Fontbonne University	159	159			
Benedictine University	160	158			
Roger Williams University	161	161			
Rensselaer Polytechnic Institute	162	163			
Milwaukee School of Engineering	163	162			
McDaniel College	164	164			
Wesleyan University	165	165			
Rhodes College	166	166			
Waynesburg University	167	167			
Salve Regina University	168	168			

Note. RE = rankings from random-effects frontier analysis; CS = rankings from average of cross-sectional frontier analysis.

Authors' Note

The July 1 cutoff is appropriate, given the Director's Cup is typically awarded at the NACDA convention in mid-June, with a potential delay until late June for institutions involved in the College World Series of Baseball (National Association of Collegiate Directors of Athletics, 2013).

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Notes

1. If schools added and subtracted particular sports strategically, increasing returns to scale might appear to hold (e.g., dropping a sport that generates few Directors' Cup points or adding a sport that is expected to generate more than proportional points). On the other hand, if a school is doing well in a particular sport, but wishes to win championships, it seems likely that diminishing returns will hold, with increasing expenditures leading to a less than proportionate increase in points earned. Overall, constant returns to scale seems likely to obtain empirically.
2. The only apparent exception, SUNY College at Buffalo, is apparent only, as the flagship SUNY Buffalo is a DI-A school.

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