CARBON EFFICIENCY OF US COLLEGES AND UNIVERSITIES: A NONPARAMETRIC ASSESSMENT

MICHAEL O'HARA AND PHILIP SIRIANNI

Abstract. Under the American College and University Presidents' Climate Commitment (ACUPCC), institutes of higher education have pledged to pursue a goal of carbon neutrality. This involves reorienting the institution's objective function to incorporate emissions as an undesirable output as well as the desirable outputs of teaching and research which have been their prior focus. A rational first step is for institutions to identify the efficiency frontier of this new objective function and evaluate their own performance relative to it. We utilize emissions reported under the ACUPCC agreement and a nonparametric Data Envelopment Analysis (DEA) approach in order to evaluate the relative performance of signatories to the agreement in terms of producing teaching and research with the least greenhouse gas emissions. We find that signatory institutions have improved their carbon efficiency since signing the agreement, and that most are now producing their desirable outputs relatively efficiently in terms of carbon emissions. We interpret this result as implying that further reductions in emissions can only be made at the cost of reducing other outputs directly or reallocating resources that might be used for desirable outputs toward reducing emissions.

JEL Classification: Q56 (Sustainability), C14 (Semiparametric and nonparametric methods)

1. Introduction

The signing of the ACUPCC agreement can be taken as a statement of a change in the university's objective function from one that does not include emissions at all, to one that treats emissions as an undesirable output to be weighed against the desirable outputs of teaching and research. Although the ultimate commitment the institutions are making is to become carbon neutral, reducing emissions to net zero will come at a cost in terms of resources that might be used to produce the desired outputs. Therefore, an important first step in this transition is for the institution to make sure it is producing efficiently, in the sense of producing its desirable outputs at the lowest level of carbon emissions possible. To our knowledge, this paper represents the first attempt to assess the carbon efficiency of signatories to the ACUPCC agreement. We evaluate the efficiency of signatory institutions using four different models in order to reflect different assumptions about how an ISE might view its objective function. Our primary finding is that, while not all schools are operating efficiently in their use of inputs to produce teaching and research, most are producing on or near the environmental efficiency frontier for their level of outputs. We interpret this as implying that schools have already "picked the low-hanging fruit" in making changes to

Date: April 27, 2014.
Key words and phrases. ACUPCC, Data envelopment analysis, Range adjusted measure, Undesirable outputs.

reduce their carbon emissions, and that further reductions can only be made by directly or indirectly trading off levels of desirable outputs, either reducing teaching and research explicitly, or increasing expenditures on emissions reduction (which indirectly trades off resources that might be applied to teaching and research.)

As a check to our methodology, we compare the efficiency of charter signatories to the agreement at the time of signing to their current efficiency. Our results reveal that most institutions have improved their efficiency in the years since initial signing, reinforcing the results in our previous paper (Sirianni and O'Hara (2014)).

2. Related Literature

Following the pioneering work of Farrell (1957), Charnes, Cooper, and Rhodes (1978) propose data envelopment analysis (DEA) as a tool for evaluating the efficiency of a decision making unit (DMU). DEA offers a flexible, nonparametric approach to frontier estimation in which a DMUs efficiency is evaluated based on their own performance relative to other DMUs in the data set. Cooper, Park, and Pastor (1999) propose a range-adjusted measure (RAM DEA) for estimating technical and mix efficiency scores in additive models. Their method is fully flexible and advantageous for several reasons. First, the weights that the DMU assigns to other DMUs are data-driven and not subjective. Second, it allows us to directly estimate output shortfalls and input excesses (the slacks) for each DMU. Third, efficiency scores are normalized and are thus invariant to units and certain translations. However, due to the way in which the data-driven weights are constructed, one clear disadvantage of this as well as any standard DEA approach is that statistical inference cannot straightforwardly be conducted. Unlike stochastic frontier analysis (SFA), which requires assumptions regarding the functional form of the objective function, there are no residuals to be estimated, and confidence bounds cannot be placed on efficiency scores without utilizing bootstrapping techniques (see, for example, Simar and Wilson (1998) and Kneip, Simar, and Wilson (2008)).

SFA, DEA, and other nonparametric methods have been widely used and refined to measure efficiency of DMUs in many contexts, including universities in the U.K. (Tomkins and Green (1988); Johnes (2006); Glass, McKillop, and ORourke (1998); Athanassopoulos and Shale (1997)), the U.S. (Cohn, Rhine, and Santos (1989)), Australia (Abbott and Doucouliagos (2003)), and Germany (Kempkes and Pohl (2010)) just to name a few. The inability to directly compute standard errors in DEA as described above is addressed by Agastini and Johnes (2010), who employ an SFA random parameters model to estimate efficiencies in a sample of Italian universities. McMillan and Chan (2006) assess the efficiency of a sample of Canadian universities using both DEA and SFA. They find that efficiency scores vary greatly depending on which methodology is employed. Furthermore, they demonstrate that the scores are very sensitive not only to the methodology but also to slight changes in how objectives are specified, thus highlighting the need for caution when making policy recommendations. Although there is no widely accepted or standardized criteria for choosing between these methodologies, universities are in effect producers of multiple outputs, and thus DEA seems to be a suitable approach. However, Kempkes and Pohl (2010) argue that SFA is more appropriate since universities are too diverse to utilize DEA and nonparametric methods in general.

In order to evaluate environmental efficiency, undesirable outputs must be added to the output mix. Using a nonparametric approach, Fare, Grosskopf, Lovell, and Pasurka (1998) develop a productivity index that uses quantities of undesirable outputs (emissions). In the presence of environmental regulation, their results suggest that productivity measures that ignore emissions are grossly misleading. Fare, Grosskopf, and Pasurka (2007a, 2007b) link the environmental production function to environmental distance functions under the assumption that firms wish to increase the production of desirable outputs while simultaneously decreasing the production of bad outputs, and compare the productivity measures when emissions are regulated versus unregulated. This approach is adopted by Macpherson, Principe, and Smith (2010) to examine watersheds in the mid-Atlantic region. Picazo-Tadeo, Reig-Martinez, and Hernandez-Sancho (2005) also utilize a directional distance function approach to examine the restriction on outputs imposed by environmental regulation. They model the firms' optimization problem by assuming that firms, under regulation, maximize the production of desirable outputs and minimize inputs under a constraint of holding undesirable outputs constant. This allows them to measure the costs of regulation as a loss in desirable outputs. However, it does not seem to be an appropriate way to think about the problem of colleges and universities, since it is more likely that they will wish to reduce undesirable outputs while holding desirable outputs constant at current levels.

To characterize the possible objectives of universities, we propose several models similar to those described in Jahanshahloo, Lofti, Maddahi, and Jafari (2012) in which operational and environmental efficiency are linked in a RAM DEA framework. Namely, the DMU may wish to become operationally efficient, environmentally efficient, or both. We propose a new model in this framework in which the DMU wishes to become environmentally efficient given the status quo input/output mix, and we argue that this is an appropriate way to capture the objective function of most colleges and universities that focus their efforts on campus sustainability.

3. Methodology

Following Cooper et al. (1999), we utilize a Range Adjusted Measure (RAM) of efficiency, a variant of a slacks-based model (SBM) that treats the slacks directly in the efficiency measure. Using an SBM approach has the advantage of being a non-radial measure, which allows us to avoid having to choose an input or output orientation in evaluation and having to assume that inputs or outputs change in proportion. It also allows us to analyze the slacks directly so that we can easily see how the institution could move to efficiency. Since the efficiency measures generated from SBMs are additive, they require some assumption on the weighting of inputs and outputs in the objective function. The "range adjusted" version utilizes data-driven weights based upon the range of values taken by each input and output, so that comparison and ranking among institutions can be preserved. However, the framework is flexible enough that if a school wished to be evaluated using some other weights, this would be straightforward to provide.

The general framework consists of n decision making units DMU_j, (j = 1,2,...,n), that use i inputs x_{ij} (i = 1, 2, . . . , m) to produce s desirable (good) outputs y_{rj} (r=1,2,...,s) and h undesirable (bad) outputs u_{lj} (l = 1,2,...,h). This is a flexible framework that allows us

to formulate several different models to measure efficiency, each corresponding to a different set of assumptions about how an ISE might view its objective function. We formulate two extreme models at the ends of the spectrum, one in which institutions ignore emissions, and one in which they treat emissions as equally important with the desired outputs of teaching and research. We do not consider these realistic models for signatories to the ACUPCC agreement. We also formulate two models that we consider more realistic descriptions of the objective functions of signatories, depending on how they view their current levels of desirable outputs. We explain the structure and intuition behind each model in the subsections below.

3.1. **Operational Efficiency.** Our first model assumes that institutions do not care about their emissions, so that the undesirable output of carbon emissions does not enter into the objective function. This could be viewed as the situation prior to singing the ACUPCC agreement. Of course, institutions might care about emissions prior to signing, but this just means that they would be evaluated under one of the following models. We still do not want to assume that all universities are currently efficient in their production of teaching and research. Therefore, we first evaluate institutions without considering the undesirable output. We call this model *operational efficiency*. For evaluating DMU p, it takes the form:

$$Max \sum_{r=1}^{s} R_r^g s_r^g + \sum_{i=1}^{m} R_i^x s_i^x \tag{1}$$

s.t.

$$\begin{aligned}
\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^x &= x_{ip} \qquad (i = 1, ..., m) \\
\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^g &= y_{rp} \qquad (r = 1, ..., s) \\
\sum_{j=1}^{n} \lambda_j &= 1 \\
\lambda_j &\geq 0 \qquad (j = 1, ..., n) \\
s_i^x &\geq 0 \qquad (i = 1, ..., m) \\
s_r^g &\geq 0 \qquad (r = 1, ..., s)
\end{aligned}$$

Here s_r^g are the slacks in good output r, and s_i^x are the slacks in input i. These are summed across all inputs and good outputs. The R_r^g and R_i^x are the weights assigned to each output and input in the objective function. Here, using the RAM approach, we define $R_r^g = \frac{1}{(m+s)(\bar{y}_r - \underline{y}_r)}$ where $\bar{y}_r = max_j(y_{rj})$ and $\underline{y}_r = min_j(y_{rj})$. Likewise, $R_i^x = \frac{1}{(m+s)(\bar{x}_i - \underline{x}_i)}$. The λ_j are so-called "intensity" parameters, and the summation terms in the first two constraints define a benchmark in the dimensions of the inputs and good outputs respectively. This benchmark can be viewed as a weighted combination of schools in the evaluation set, and the two constraints define the relationship between the benchmark, the slacks, and the observed values of inputs and outputs of DMU p.

The measure of efficiency Γ is computed as

$$\Gamma = 1 - \left(\sum_{r=1}^{s} R_r^g s_r^{g*} + \sum_{i=1}^{m} R_i^x s_i^{x*} \right) \tag{2}$$

where * indicates the optimal values.

3.2. **Environmental Efficiency.** Our primary goal is to evaluate the environmental efficiency of the ISEs in our sample, by which we mean the excess in carbon emissions the schools generates relative to its benchmark. For our first model, we assume that the institution wants to attain operational efficiency, and then wants to produce that level of output at the least possible emissions. We believe this is a realistic view of the way ISEs would view their objective function. The model takes the form

$$Max \sum_{r=1}^{s} R_r^g s_r^g + \sum_{i=1}^{m} R_i^x s_i^x + \varepsilon(\sum_{l=1}^{h} R_l^b s_l^b) \tag{3}$$

s.t.

$$\begin{aligned}
\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^x &= x_{ip} \qquad (i = 1, ..., m) \\
\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^g &= y_{rp} \qquad (r = 1, ..., s) \\
\sum_{j=1}^{n} u_{lj}\lambda_j + s_l^b &= u_{lp} \qquad (l = 1, ..., h) \\
\sum_{j=1}^{n} ND_{qj}\lambda_j &= nd_{lp} \qquad (q = 1, ..., nd) \\
\sum_{j=1}^{n} \lambda_j &= 1 \\
\lambda_j &\geq 0 \qquad (j = 1, ..., n) \\
s_i^x &\geq 0 \qquad (i = 1, ..., m) \\
s_r^g &\geq 0 \qquad (r = 1, ..., s) \\
s_l^b &\geq 0 \qquad (l = 1, ..., h)
\end{aligned}$$

Note here the inclusion of two non-discretionary variables in the form of the number of heating degree days (HDD) and cooling degree days (CDD) at the state level in which the institution is located. The purpose of this is to capture the effect of climatic conditions in the emissions of institutions. A school in, for example, a very cold area where heat is needed many months of the year will produce more emissions for the same levels of teaching and research output, but we do not feel that this should be seen as indicative of inefficiency. These variables are not allowed slacks, so that schools will be compared to a benchmark

institution with the same number of heating and cooling days in the year. In practice, the more constraints that are placed on the model, the more schools will be measured to be efficient, but we feel that it would be misleading in this case to leave out this constraint. We leave these variables out of the model for operational efficiency since if emissions are not being considered, then it does not make sense to restrict the benchmark school to have the same climate as the one being evaluated. But they are included in all models that evaluate emissions.

The $\varepsilon > 0$ here is a non-Archimedean element smaller than *any* positive real number (and remaining so when multiplied by any positive real number). In practical terms, this puts very small, but nonzero, weight on the second term while making sure it is still included in the objective function.

In computation, the effect is that the optimization is performed over the first two terms constituting operational efficiency first, and then the undesirable emissions are evaluated from there. The algorithm first reduces the problem to Model (1) and solves for the values of λ_j that constitute the benchmark for school p in the y and x dimensions. In a second stage, the levels of inputs and good outputs are then set at the benchmark values, such that $s_i^x = s_r^g = 0$. This constrains the values of λ_j that can be chosen in the second stage so that a benchmark for the bad outputs can only be chosen among the schools that meet the benchmark for y and x. If school p is operationally inefficient, then the good outputs of the benchmark will be greater (or at least no less) than those of school p and the inputs will be less (or no greater). Since the benchmark has greater good outputs and/or less inputs, the benchmark would also be presumed to have more emissions than school p. That is, $\sum_{j=1}^{n} u_{lj}\lambda_j$ would be expected to be larger than u_{lp}, but in a way that is proportional to the increase in outputs or the decrease in inputs. Therefore, using this procedure will only result in an efficiency score less than 1 if ISE p currently has emissions that are larger than they should be if inputs and good outputs change in proportion from the benchmark. The efficiency scores that result should then be interpreted as meaning that if the school moved first to operational efficiency, and increased its emissions from current levels in proportion to this move, this is the inefficiency that would still be present relative to the benchmark.

As an alternative, we also evaluate institutions' environmental efficiency from their current levels of inputs and desirable outputs. In other words, assuming the institution wishes to continue the status quo of their input and output profile, are they doing it efficiently in terms of carbon emissions? Thus the model becomes

$$Max \sum_{l=1}^{h} R_l^b s_l^b \tag{4}$$

s.t.

$$\begin{aligned}
\sum_{j=1}^{n} x_{ij}\lambda_j &= x_{ip}^0 \qquad (i = 1, ..., m) \\
\sum_{j=1}^{n} y_{rj}\lambda_j &= y_{rp}^0 \qquad (r = 1, ..., s) \\
\sum_{j=1}^{n} u_{lj}\lambda_j + s_l^b &= u_{lp} \qquad (l = 1, ..., h) \\
\sum_{j=1}^{n} ND_{qj}\lambda_j &= nd_{lp} \qquad (q = 1, ..., nd) \\
\sum_{j=1}^{n} \lambda_j &= 1 \\
\lambda_j &\geq 0 \qquad (j = 1, ..., n) \\
s_l^b &\geq 0 \qquad (l = 1, ..., h)
\end{aligned}$$

where x_{ip}^0 and y_{rp}^0 are DMU p's status quo levels of input i and output r respectively. Slacks on the inputs and desirable outputs are constrained to be zero. Therefore, the benchmark relative to which the school's emissions are evaluated has the school's current levels of inputs and desirable outputs. In this case, $R_l^b = \frac{1}{h}(\bar{u}_l - \underline{u}_l)$ since only bad outputs are included in the objective function.

3.3. **Total Efficiency.** Our final model evaluates the institutions under the assumption that their objective function equally weights inputs, desirable outputs, and a reduction in undesirable outputs.

$$Max \sum_{r=1}^{s} R_r^g s_r^g + \sum_{i=1}^{m} R_i^x s_i^x + \sum_{l=1}^{h} R_l^b s_l^b \tag{5}$$

s.t.

$$\begin{aligned}
\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^x &= x_{ip} && (i = 1, ..., m) \\
\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^g &= y_{rp} && (r = 1, ..., s) \\
\sum_{j=1}^{n} u_{lj}\lambda_j + s_l^b &= u_{lp} && (l = 1, ..., h) \\
\sum_{j=1}^{n} ND_{qj}\lambda_j &= nd_{lp} && (q = 1, ..., nd) \\
\sum_{j=1}^{n} \lambda_j &= 1 \\
\lambda_j &\geq 0 && (j = 1, ..., n) \\
s_i^x &\geq 0 && (i = 1, ..., m) \\
s_r^g &\geq 0 && (r = 1, ..., s) \\
s_l^b &\geq 0 && (l = 1, ..., h)
\end{aligned}$$

4. Data

We follow previous literature in our specification of the inputs and desirable outputs of ISEs. We specify our two inputs indirectly as expenditures on teaching and research using data from IPEDs. Outputs are generally divided into the broad categories of teaching and research, with service generally omitted due to a lack of good measures. The ways in which these outputs are measured varies somewhat in the literature. We go with the consensus view of measuring teaching by the total full-time equivalent (FTE) enrollment at the ISE, and research by value of research grants obtained. Enrollment data is taken from IPEDs and grant data is from MUP. The research measure in particular is highly questioned, as the emphasis on grant writing varies considerably among different types of institutions. Though recognizing this, past researchers have generally fallen back on it for lack of any better measure. The assumption is that the quantity of grants will be correlated with research activity even though it is a far from perfect measure. Since the DEA methodology by its nature allows DMUs to chose their weighting of inputs and outputs, the variation among different types of ISEs should not be a major problem. To increase comparability, we evaluate research institutions separately from Liberal Arts (Arts and Sciences in Carnegie Classification) schools.

We specify a single undesirable output, measured as total carbon emissions in Scopes 1 and 2, gathered from the ACUPCC reporting system. We follow our previous paper in omitting Scope 3 emissions. In the future, we hope to be able to treat Scope 3 and examine the efficient mix of emissions, but at present we do not believe the Scope 3 data are of sufficient quality to make reliable inference.

TABLE 1. R1 schools compared to all research institutions

Institution	OpEff	EnvEff	EnvEffStatQuo	TotEff
Arizona State University	1.0000	1.0000	1.0000	1.0000
Colorado State University-Fort Collins	1.0000	1.0000	1.0000	1.0000
Duke University	1.0000	1.0000	1.0000	1.0000
Georgia Institute of Technology-Main Campus	1.0000	1.0000	1.0000	1.0000
Mississippi State University	1.0000	1.0000	1.0000	1.0000
Montana State University	1.0000	1.0000	1.0000	1.0000
New York University	0.8142	1.0000	1.0000	1.0000
Ohio State University-Main Campus	1.0000	1.0000	1.0000	1.0000
Oregon State University	1.0000	1.0000	1.0000	1.0000
SUNY at Albany	1.0000	1.0000	1.0000	1.0000
University of Arkansas	0.9675	0.9849	1.0000	0.9556
University of California-Berkeley	1.0000	1.0000	1.0000	1.0000
University of California-Davis	0.9627	1.0000	1.0000	1.0000
University of California-Irvine	1.0000	1.0000	1.0000	1.0000
University of California-Los Angeles	1.0000	1.0000	1.0000	1.0000
University of California-Riverside	1.0000	1.0000	1.0000	1.0000
University of California-San Diego	1.0000	1.0000	1.0000	1.0000
University of Colorado Boulder	0.9663	1.0000	1.0000	1.0000
University of Connecticut	0.9163	1.0000	1.0000	0.9340
University of Illinois at Urbana-Champaign	0.9905	0.9578	0.7350	0.9446
University of Louisville	0.9498	0.9841	0.8069	0.9393
University of Maryland-College Park	0.9523	0.9944	1.0000	0.9493
University of Miami	1.0000	1.0000	1.0000	1.0000
University of Minnesota-Twin Cities	1.0000	1.0000	1.0000	1.0000
University of Missouri-Columbia	0.9673	0.9466	1.0000	0.9089
University of North Carolina at Chapel Hill	1.0000	1.0000	1.0000	1.0000
University of Oklahoma Norman Campus	0.9657	0.9932	1.0000	0.9623
University of Tennessee	0.8873	0.9974	1.0000	0.8930
Virginia Commonwealth University	0.9713	1.0000	0.9479	0.9804
Washington State University	1.0000	1.0000	1.0000	1.0000
Yeshiva University	0.9369	1.0000	1.0000	0.9533

Our two non-discretionary variables are the number of heating degree days (HDD) and cooling degree days (CDD) at the state level in which the institution is located. These are obtained from NOAA, and are matched to the reporting period of the emissions from ACUPCC, so that emissions, HDD and CDD are all covering the same period.

5. RESULTS

Table (1) lists the R1 institutions in our dataset and evaluates them relative to all research schools. They are separated by table only for easier viewing. Table (6) shows summaries of

TABLE 2. R2 schools compared to all research institutions

Institution	OpEff	EnvEff	EnvEffStatQuo	TotEff
Ball State University	1.0000	1.0000	1.0000	1.0000
Cleveland State University	1.0000	1.0000	1.0000	1.0000
Drexel University	0.9662	1.0000	1.0000	1.0000
George Mason University	0.9840	1.0000	0.9855	0.9876
Missouri University of Science and Technology	0.9799	0.9911	0.9377	0.9748
New Mexico State University-Main Campus	0.9942	1.0000	1.0000	1.0000
Northeastern University	1.0000	1.0000	1.0000	1.0000
Ohio University-Main Campus	1.0000	1.0000	1.0000	1.0000
SUNY at Binghamton	1.0000	1.0000	1.0000	1.0000
Syracuse University	0.9753	0.9981	1.0000	0.9740
Temple University	1.0000	1.0000	1.0000	1.0000
University of Maryland-Baltimore County	0.9799	1.0000	0.9542	0.9854
University of Massachusetts-Lowell	0.9974	1.0000	1.0000	1.0000
University of Missouri-Kansas City	0.9710	1.0000	1.0000	0.9832
University of New Hampshire-Main Campus	0.9723	1.0000	1.0000	1.0000
University of North Texas	1.0000	1.0000	1.0000	1.0000
University of Vermont	0.9773	1.0000	1.0000	0.9825
Utah State University	1.0000	1.0000	1.0000	1.0000

the tables for the different groups of institutions. The institutions vary in their operational efficiency, with NYU having the lowest score at 0.81, and as shown in Table (6), 58% are operationally efficient. Those schools that are inefficient are not far off though, with an average efficiency of 0.93. In environmental terms, the majority of the R1 schools have a score of 1. Only five have scores less than 1 whether or not we assume they move first to operational efficiency. Interestingly, they are not exactly the same set of schools in each case. Virginia Commonwealth is efficient when moving to operational efficiency first, but not so at the status quo, and vice versa for the University of Oklahoma Norman Campus, although they are very close.

Table (2) shows the data for R2 schools. More of these institutions are measured as operationally inefficient, with only 45% being rated efficient. This is to be expected, as they are being compared to R1 schools, which have the same goals but are generally producing more research output. The variance is smaller, however, with an average efficiency of 0.98 for those not achieving full efficiency. In terms of environmental efficiency, the R2s are still doing well when optimizing operational efficiency first, though only 75% are efficient when evaluated at the status quo.

Table (3) shows the results for the Liberal Arts colleges in our dataset. Liberal Arts schools are operating, on average, at a high degree of operational inefficiency, all but one are environmentally efficient, with Gettysburg College standing out as the only inefficient school. The total efficiency scores here mostly reflect operational inefficiencies. More insight can be gained by analyzing the slacks shown in Table (4). In most cases, schools are being

TABLE 3. Liberal Arts colleges

Institution	OpEff	EnvEff	EnvEffStatQuo	TotEff
Bowdoin College	1.0000	1.0000	1.0000	1.0000
Colby College	1.0000	1.0000	1.0000	1.0000
Colgate University	1.0000	1.0000	1.0000	1.0000
College of the Holy Cross	1.0000	1.0000	1.0000	1.0000
DePauw University	1.0000	1.0000	1.0000	1.0000
Dickinson College	0.9410	1.0000	0.9859	0.9617
Eckerd College	1.0000	1.0000	1.0000	1.0000
Furman University	1.0000	1.0000	1.0000	1.0000
Gettysburg College	0.9886	1.0000	0.9250	0.9850
Goucher College	0.9435	1.0000	1.0000	1.0000
Hamilton College	0.8385	1.0000	1.0000	0.8554
Hampshire College	1.0000	1.0000	1.0000	1.0000
Haverford College	1.0000	1.0000	1.0000	1.0000
Hobart William Smith Colleges	1.0000	1.0000	1.0000	1.0000
Luther College	1.0000	1.0000	1.0000	1.0000
Pitzer College	1.0000	1.0000	1.0000	1.0000
Pomona College	1.0000	1.0000	1.0000	1.0000
Saint Johns University	1.0000	1.0000	1.0000	1.0000
University of Puget Sound	1.0000	1.0000	1.0000	1.0000
Washington and Jefferson College	1.0000	1.0000	1.0000	1.0000
Washington and Lee University	0.8249	0.9771	1.0000	0.7873
Wesleyan University	1.0000	1.0000	1.0000	1.0000

evaluated as inefficient due to levels of research expenditure too high to be justified by the output. The high number of efficient scores

Tables (7) and (8) compare the efficiency scores of institutions in 2007, the charter year of the ACUPCC agreement, with their scores in 2011, based upon a Malmquist Index measure. The Malmquist index can be broken down into indices for the technical change of the institution (the movement toward the frontier), and the technical change (the shift in the frontier). A number greater than 1 indicates progress, while a number less than 1 indicates regress. The sample sizes are very limited due to the fact that many of the institutions who are signatories in 2011 were not charter members, and that institutions are only required to submit a report every two years, so that many charter signatories do not report in 2011. Of the few schools that show change here, all indicate progress toward efficiency since signing the agreement. Interestingly, the data indicate regression of the frontier itself. At present, we do not have an explanation for this, but due to the very limited sample size available, we are hesitant to draw conclusions at this time.

TABLE 4. Optimal slacks: Liberal Arts colleges under Total Efficiency

InstrExp	ResExp	FTE	ResGrants	Emissions	InstrExp
Bowdoin College	0	0	0	0	0
Colby College	0	0	0	0	0
Colgate University	0	0	0	0	0
College of the Holy Cross	0	0	0	0	0
DePauw University	0	0	0	0	0
Dickinson College	0	1301	78	0	806
Eckerd College	0	0	0	0	0
Furman University	0	0	0	0	0
Gettysburg College	0	0	0	0	1935
Goucher College	0	0	0	0	0
Hamilton College	0	135	950	1	4442
Hampshire College	0	0	0	0	0
Haverford College	0	0	0	0	0
Hobart William Smith Colleges	0	0	0	0	0
Luther College	0	0	0	0	0
Pitzer College	0	0	0	0	0
Pomona College	0	0	0	0	0
Saint Johns University	0	0	0	0	0
University of Puget Sound	0	0	0	0	0
Washington and Jefferson College	0	0	0	0	0
Washington and Lee University	16221	1577	208	1	11506
Wesleyan University	0	0	0	0	0

TABLE 5. Summary of models

	OpEff	EnvEff	EnvEffStatQuo	TotEff
R1 schools				
Proportion efficient	0.58	0.87	0.84	0.68
Mean efficiency	0.93	0.98	0.83	0.94
R2 schools				
Proportion efficient	0.45	0.95	0.75	0.60
Mean efficiency	0.98	0.99	0.97	0.98
Lib Arts schools				
Proportion efficient	0.71	1.00	0.95	0.76
Mean efficiency	0.83	NaN	0.91	0.88

TABLE 6. Summary of models

row.names	OpEff	EnvEff	EnvEffStatQuo	TotEff
R1 schools				
Proportion efficient	0.58	0.77	0.90	0.68
Mean efficiency	0.94	0.98	0.83	0.94
R2 schools				
Proportion efficient	0.44	0.89	0.83	0.67
Mean efficiency	0.98	0.99	0.96	0.98
Lib Arts schools				
Proportion efficient	0.77	0.95	0.91	0.82
Mean efficiency	0.91	0.98	0.96	0.90

TABLE 7. Change in environmental efficiency: research institutions

Institution	eff.change	tech.change	Malmquist
Colorado State University-Fort Collins	1.0000	1.0000	1.0000
Duke University	1.0000	1.0000	1.0000
George Mason University	1.0365	0.9647	0.9997
Georgia Institute of Technology-Main Campus	1.0000	1.0000	1.0000
New York University	1.0000	1.0000	1.0000
Northeastern University	1.0239	0.9738	0.9942
Oregon State University	1.0495	0.9121	0.9164
Temple University	1.0000	0.9417	0.8868
The University of Tennessee	1.0000	0.8715	0.7596
University of Missouri-Columbia	1.0000	1.0000	1.0000
University of North Carolina at Chapel Hill	1.2706	0.8871	1.2706
University of Vermont	1.0470	0.9463	0.9818
Utah State University	1.0000	0.9860	0.9723

6. CONCLUSION

Stay tuned.

TABLE 8. Change in environmental efficiency: Liberal Arts schools

Institution	eff.change	tech.change	Malmquist
Bowdoin College	0.9225	0.7375	0.4629
College of the Holy Cross	1.0000	1.0000	1.0000
Dickinson College	1.0699	0.9668	1.0699
Eckerd College	1.0000	1.0000	1.0000
Furman University	1.0000	1.0000	1.0000
Hamilton College	1.0000	1.0000	1.0000
Luther College	1.0000	1.0000	1.0000
Pomona College	1.0000	1.0000	1.0000
Saint Johns University	1.0000	1.0000	1.0000
Washington and Lee University	1.0000	1.0000	1.0000

REFERENCES

Abbott, M. and C. Doucouliagos (2003). "The efficiency of Australian universities: A data envelopment analysis." *Economics of Education Review*, 22(1): 89-97.

Agasisti, T. and G. Johnes (2010). "Heterogeneity and the evaluation of efficiency: The case of Italian universities". *Applied Economics*, 42(11): 1365 - 1375.

Assessing the comparative efficiency of higher education institutions in the U.K. by means of data envelopment analysis." *Education Economics*, 5(2): 117-134.

Charnes, A., Cooper, W., and E. Rhodes (1978). "Measuring efficiency of decision marking units." *European Journal of Operational Research*, 2: 429-444.

Cohn, E., S. Rhine, and M. Santos (1989). "Institutions of higher education as multi-product firms: Economies of scale and scope". *Review of Economics and Statistics*, 71(2): 284 - 290.

Cooper, W., K. S. Park, and J. Pastor (1999). "RAM: A Range Adjusted Measure of inefficiency for use with additive models, and relations to other models and measures in DEA". *Journal of Productivity Analysis* 11(1): 5-42.

Färe, R., F. Grosskopf, C. Lovell, and C. Pasurka (1989). "Multilateral productivity comparisons when some outputs are undesirable: A nonparametric approach". *Review of Economics and Statistics*, 71(1): 90 - 98.

Färe, R., Grosskopf, S., Pasurka, C.A., 2007a. Environmental production functions and environmental directional distance functions. *Energy*, 32(7): 1055-1066.

Färe, R., Grosskopf, S., Pasurka, C.A., 2007b. Pollution abatement activities and traditional productivity. *Ecological Economics*, 62(3), 673-682.

Farrell, M. (1957). "The measurement of productive efficiency." *Journal of the Royal Statistical Society*, 120(3): 253-290.

Glass, J., D. McKillop, and G. O'Rourke (1998). "A cost indirect evaluation of productivity change in UK universities". *Journal of Productivity Analysis*, 10: 153 - 175.

Jahanshahloo, G., Lofti, F., Maddahi, R., and Y. Jafari (2012). "Efficiency and benchmarking in the presence of undesirable (bad) outputs: A DEA approach". *International Journal of Applied Mathematical Research*, 1(2): 178-188.

Johnes, J. (2004). "Efficiency measurement." In Johnes, G. and J. Johnes (Eds.), *The International Handbook on the Economics of Education*, Cheltenham: Edward Elgar.

Johnes, J. (2006). "Data envelopment analysis and its application to the measurement of efficiency in higher education." *Economics of Education Review*, 25: 273-288.

Kneip, A., Simar, L., and P. Wilson (2008). "Asymptotics and consistent bootstraps for DEA estimators in nonparametric frontier models." *Econometric Theory*, 24: 1663-1697.

Kempkes, G., and C. Pohl (2010). "The efficiency of German universities: Some evidence from nonparametric and parametric methods". *Applied Economics*, 42(16): 2063 - 2079.

Macpherson, A., P. Principe, and E. Smith (2010). "A directional distance function approach to regional environmentaleconomic assessments". *Ecological Economics*, 69: 1918-1925.

McMillan, M., and W. Chan (2006). "University efficiency: A comparison of results from stochastic and non-stochastic methods". *Education Economics*, 14(1): 1 - 30.

Picazo-Tadeo, A., Reig-Martinez, E., and F. Hernandez-Sancho (2005). "Directional distance functions and environmental regulation". *Resource and Energy Economics*, 27: 131-142.

Simar, L. and P. Wilson (2008). "Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models." *Management Science*, 44(1): 49-61.

Sirianni, P. and M. O'Hara (2014). "Do actions speak as loud as words? Commitments to 'going green' on campus. *Contemporary Economic Policy*, forthcoming.

Tomkins, C. and Green, R. "An experient in the use of data envelopment analysis for evaluating the efficiency of U.K. university departments of accounting." *Financial Accountability and Management*, 4: 147-164.

Department of Economics, Colgate University, 13 Oak Dr., Hamilton, NY 13346,
E-mail address: mohara@colgate.edu

Department of Economics, Finance, and Accounting, State University of New York at Oneonta, 108 Ravine Pkwy, Oneonta, NY 13820,
E-mail address: philip.sirianni@oneonta.edu