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# Frontier and envelopment evaluations of university graduation efficiencies and productivities: elements for performance-based funding


## Abstract

Universities are increasingly being pressured to increase student graduation rates. In the public sector, graduation rates are being integrated into performance based funding models. To some extent, private university rates have acted as benchmarks for public institutions. Thus, there is a managerial and public policies need to better understand productive efficiencies of both private and publicly owned universities. Thus, this paper provides stochastic frontier analysis (SFA) and data envelopment analysis (DEA) estimates and comparisons of graduation rate efficiencies and productivities across both sectors. Panel data is used for four academic years from 2005 to 2009, and includes possible effects and responses to the financial crisis. Although both sectors operate below 85% efficiency, results indicate private universities operate from 2 percentage points below to 7 to 12 percentage points above public institutions. Malmquist index results indicate overall productivity erosion for both ownership types. That is due, in part, to declines in managerial efficiencies and technological changes. However, total productivity regress is not substantially different in two sectors and there is some indication that all universities are moving toward productivity gain territory despite the underlying burdens imposed by the financial crisis.


**Keywords:** frontier analysis, envelopment analysis, efficiency, productivity, universities.
**JEL Classification:** D20, I21, I22, I23, L30, C33.

## Introduction

Stochastic frontier analysis (SFA) and data envelopment analysis (DEA) have been used as the standard techniques for evaluating the operating efficiencies of firms, institutions, and agencies. This paper employs those techniques to evaluate and compare the efficiency and productivity changes of private and public universities in producing the educational success of students. That success is measured by graduation rates. It is those rates that are becoming increasingly important as public higher education moves toward performance based financing with taxpayer provided funding tied to student academic success as opposed to institutional enrollments (Dougherty and Reddy, 2011). In the political arena, that has brought into question the lower graduation successes of public universities in comparison to their private counterparts. Moreover, the global financial crisis has heightened the political interest in public management reforms with an eye toward greater privatization of the public provision of goods and services. In the United States, that has translated into increased managerial pressures to improve operating efficiencies of public universities.

This paper explores those managerial responses and compares public university efficiency outcomes relative to private university benchmarks. The rigor offered by employing SFA and DEA techniques in this capacity could serve as elements in public higher education funding systems and models.

The empirical evaluations begin with the estimation of stochastic production frontiers for private and public universities. The frontiers provide insights into the effects of student, faculty, and university characteristics on graduation rates while also testing for the presence of university inefficiencies in production. Technical efficiencies derived from the stochastic frontier estimates are compared to estimates of output-oriented data envelopment efficiencies. The analyses are based on panel data observations on U.S. Carnegie classified master's universities over four academic years, 2005-2009, that span pre and post financial crisis period. Thus, operating efficiencies are compared over time for both private and public university sectors. The panel data structure is also used to estimate Malmquist productivity indices along with the associated decompositions so as to examine changes in university managerial efficiency and in production technology.

The next section of the paper provides an applied literature survey. That is followed by a section establishing the SFA and DEA methodologies, a data description section, and a section presenting the empirical results. The final section contains a summary and concluding remarks.

## 1. Literature survey

The emphasis of this paper is on empirical applications of SFA and DEA to investigations regarding higher education graduation rates. The paper cannot begin to review the theoretical development of SFA or DEA or the volume of research that has been produced in estimation of production and cost frontiers. In the DEA literature alone, a recent review puts the number of published DEA research papers at 4000 (Emrouznejad et al., 2008). Of course, it is appropriate to recognize that the founding of SFA is universally accepted as being jointly due to Aigner et al. (1977) and Meeusen and van der Broech (1977) while the seminal work of Charnes et al. (1978) gave us DEA. The many developments and contributions that followed those pioneering works are well documented elsewhere, including Coelli et al., (2005) and Kumbhakar and Lovell (2003), Cooper et al. (2007) and Cook and Zhu (2008). A literature review pertaining to the present empirical focus revealed a substantially smaller body of research.

Published research related to SFA efficiency estimates of universities is fairly new and small in number. Izadi et al. (2002) estimated efficiencies of British universities. They used a 1994-95 academic year cross sectional data of 99 universities. For 80 English and Welsh university efficiencies, Stevens (2005) employed panel data covering 1995-1999 academic years. Following that study, 2000-2001 academic years were included in the Johnes and Johnes (2009) stochastic analysis of 121 English institutions. The McMillan and Chan (2006) study of 45 Canadian universities used data actually dating back to the 1992 academic year. Abbott and Doucouliagos (2009) compared 1997-2003 efficiencies of 7 New Zealand universities to 36 Australian universities. For the U.S. higher education, 2005-09 efficiency estimates exist for 159 American public universities (Sav, 2012a), 222 faith related institutions (Sav, 2012b), and 8 private and 28 public ivy universities (Sav, 2012c). The modeling and data variations existing among these studies make any brief comparisons unmanageable. Suffice to say that the reported university operating efficiency scores range from approximately 0.25 to 1.0 or 25% to 100% efficiency.

DEA studies related to university level efficiency evaluations appeared somewhat earlier than the SFA studies. The first six studies to appear in the literature employed cross sectional data. Ahn et al. (1988) and Breu et al. (1994) applied DEA to U.S. higher education using 1984 and 1992 academic year data. Two studies of the United Kingdom universities, Athannassapoulos and Shale (1997) and Glass et al. (2006), used production related data from 1992 and 1996. Avkiran (2001) provided efficiency estimates for 1995 Australian universities and McMillan and Chan (2006) did so for 1992 Canadian universities. Efficiency scores among these studies range from a minimum of 0.14 to 1.0.

Beginning from 2007 DEA studies of higher education turned to the use of panel data and made use of the Malmquist index to evaluate university productivity changes over time. Three studies were published between 2007 and 2009. Castano and Cabanda (2007) used 1999-2003 academic years in their efficiency study of 59 Philippine universities. Adding an earlier academic year to that list, Worthington and Lee (2008) investigated 35 Australian universities. Agasisti and Johnes (2009) provided efficiency comparisons between 57 Italian and 127 English universities. Productivity estimates emanating from these studies range from a productivity regress of approximately 8% to a productivity growth of 30%.

Of all above studies, only the McMillan and Chan (2006) study used both SFA and DEA models to fashion comparisons of operating efficiencies across techniques. However, since their estimates were based on cross sectional data, their study could not be extended to evaluate efficiency or productivity changes over time. Those insights require longitudinal data.

While SFA and DEA methodologies and applications are the emphasis of the current paper, it is also recognized that a number of other studies use standard econometric methods in investigating university graduation rates. Webber and Ehrenberg (2010) examined the effects of instructional expenditures on college wide graduation rates. Others have addressed the impact of tenured faculty vs. adjunct faculty hiring on degree completions (Ehrenberg and Zhang, 2005; and Bettinger and Long, 2010). In the empirical analysis to follow, the main thrust of these studies will also be utilized by including university expenditure allocation and faculty employment status effects in the modeling of university production frontiers.

## 2. Efficiency and productivity methodology

Using standard notation, the stochastic production frontier for panel data observations on $i = 1,\dots, N$ firms, agencies, or institutions over $t = 1,\dots,T$ time periods can be expressed as

$$Y_{it} = \exp(x_{it}\beta + v_{it} - u_{it}), \quad (1)$$

where $Y$ is the production of the $i$th unit in the $t$th time period, $x$ is a vector of inputs, and the $\beta$ are corresponding parameters to be estimated. $v$ are the usual random variables that affect production and are beyond the control of the institution. They are assumed to identically and independently distributed as a normal distribution with zero mean and variance $\sigma^2_v$. In contrast to the random effects on production, $u$ are nonnegative measures of the technical inefficiencies that can be due to input characteristics or managerial decision-making within the institution. Although many distributional assumptions can be employed for the inefficiency term, the half normal and truncated normal are the most widely used. The latter is a more general distribution and will, therefore, be employed here. Thus, $u$ follow a normal distribution with mean $\mu$ and variance $\sigma^2_u$. With the Battese and Coelli (1992) time varying technical efficiency model,

$$u_{it} = u_i(-\eta(t-T)), \tag{2}$$

where $\eta$ represents the time parameter to be estimated for the inefficiency effects; if it is positive (negative) then inefficiency in production decreases (increases) with time. The individual firm's technical efficiency, *TE,* is determined relative to the production frontier, i.e., its production with its inefficiency present relative to production with inefficiency being removed:

$$TE_i = E(Y_{it} \mid u_i) / E(Y_{it} \mid u_i = 0). \tag{3}$$

Thus, *TE* varies in the range of 0 to 1 with the latter being the fully efficient firms resting on the production frontier. A value of 0.75 would be indicative of a firm that is 75% efficient or is producing only 75% of its production possibility.

Empirical implementation of the SFA model requires the specification of a functional form for the underlying production technology. Many such forms are available. Due to estimation issues associated with the failure of convergence, the translog specification could not be used in the present empirical work. Thus, the widely used Cobb-Douglas production function is adopted.

In contrast, non-parametric DEA models do not require a functional form for the production technology. As a mathematical programing approach, DEA constructs a piece-wise linear production surface representing the best practice production frontier arising from output and input observations on a group of decision-making units or DMUs (Charnes, et al., 1978). The resulting frontier consists of efficient DMUs and envelops the other relatively inefficient DMUs.

Since the present empirical interest is in knowing whether or not colleges are producing the maximum graduation rates given their inputs, the output-oriented DEA approach, as opposed to the input-oriented approach, is appropriate. The constant returns to scale (CRS) DEA model due to Charnes et al. (1978) can be expressed for the DMU producing an output, $y$, using $k = 1, \ldots, K$ inputs as

$$\max_{\phi_i \lambda_j} \phi_i \tag{4}$$

subject to

$$\begin{aligned} & Y\lambda - \phi y_{it} \geq 0, \\ & -X\lambda + x_{it} \geq 0, \\ & \lambda \geq 0, \end{aligned} \tag{5}$$

where the $Y$ and $X$ are output and input matrices, respectively. For convenience, the input and output slacks that can be attached to the model have been omitted (e.g., see Cook and Zhu, 2008). Due to the work of Banker et al. (1984), greater flexibility is introduced into the model by allowing variable returns to scale (VRS): the constraint that the sum of the $\lambda$ equal one is added to the above.

In the above, $\phi - 1$, where $\phi \geq 1$, is a measure of the relative increase in output that is possible for the given institution. Thus, the technical efficiency (*TE*) with which each unit operates is based on its actual production accomplishment relative to its potential production level for the frontier. Thus,

$$TE = y / \phi y = 1/\phi. \tag{6}$$

As an efficiency score *TE* is in the range $0 \leq TE \leq 1$ with the value of one representing an efficient unit that is operating on the frontier.

When panel data are available, DEA is useful for measuring efficiency changes over time. The Malmquist index, originally due to Malmquist (1953), allows those changes to be separately accounted for as (1) changes in institutional operating efficiencies under a fixed production technology and (2) changes that occur as a result of technological progress. The total productivity change is thus measured as changes in institutional distances (*D*) from a fixed frontier and changes in institutional distances (*D*) from a moving frontier (e.g., Fare et al., 1994). The productivity index (*M*) for year $t + 1$ relative to year $t$ is (e.g., Cooper et al., 2004; and Cook and Zhu, 2008):

$$M_0(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} \left[ \left( \frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^{t+1}, y^{t+1})} \right) \left( \frac{D_0^t(x^t, y^t)}{D_0^{t+1}(x^t, y^t)} \right) \right]^{\frac{1}{2}}. \tag{7}$$

Based on $M$, there can occur total productivity gains, $M > 1$, or regress $M < 1$. The total is decomposed into two components. The first component on the right side of M measures the technical efficiency change as the relative distance (*D*) between actual and efficient production. For CRS, that efficiency change can be further decomposed into pure technical or management efficiency and scale efficiency. The second geometric mean component measures the technological change, i.e., the shift in the production frontier. In preliminary tests of the SFA production function, separate estimates were generated for private universities and public universities. Based on Chow tests, it was verified that statistically significant (*F*-value was 21.64) structural differences exist between the two sectors. That is consistent with the findings presented in the seminal work of Cohn et al. (1989) and like that work and the many to follow, the present paper proceeds with separate private and public sector estimates for both the SFA and DEA models.

## 3. University data

Data for individual universities are drawn from the Integrated Postsecondary Education Data System (IPEDS), U.S. Department of Education. The data are a balanced panel for the four academic years 2005-09 and include 198 private not-for-profit universities and 216 publicly owned and operated universities. Some of these institutions carry the name "college" but for the purposes of this paper they are referred to as "universities". All the institutions have the identical Carnegie classification. They are classified as "Master's Colleges and Universities" and engage heavily in undergraduate education and award at least 50 master's degrees but fewer than 20 doctoral degrees each academic year. Since the interest lies in baccalaureate graduation rates, the university flagships and higher level research intensive and doctoral classified universities are not included in the sample.

University output is measured as the undergraduate graduation rate (*GRAD-RATE*). The rate used from *IPEDS* is the percentage of students that have graduated within a six year time frame from entry into the university. The rate is based on cohort degree completions within 150% of the normal time to degree completion. Following the applied work reviewed in this paper, it is assumed that a university's graduation rate success depends upon a number of institutional, student, and faculty inputs and characteristics.

On the input side, the total twelve month unduplicated undergraduate student headcount enrollment (*UGRD*) is used as a possible measure of the enrollment size effect on graduation rates. In addition, some students enter higher education from low income underfunded primary and secondary school districts and may, therefore, be less academically prepared. To control for that possible effect on graduation rates, included is the percentage of students enrolled on government funded low income grants (*LOWINC*). In addition, total graduate twelve month unduplicated headcount enrollment (*GRD*) is included to measure the presence of graduate program education at the institution and its possible effect on undergraduate graduation rates. It may be possible that an institutional focus on graduate program development competes with or enhances attention to undergraduate education.

The total number of faculty employed (*FACULTY*) serves at the direct measure of labor input on the teaching and research front. As a productivity measure, the average faculty salary (*SALARY*) is included as a wage variable. As with previous studies, faculty research is proxied by the institutional revenue from grants and contracts. It is calculated here as research per faculty member (*RESCH*) acts as an input into university production. To include possible effects on graduation successes that might arise from tenured faculty vs. non-tenure track faculty employment, the percentage of faculty that are tenured (*TENURE*) is included along with the percentage of faculty that are employed in non-tenure track positions (*NTRACK*). The latter is intended to capture all non-tenure track faculty employment, including instructor ranks and adjunct employment. Two additional measures are included in the analysis: (1) university expenditures on student support services per undergraduate student (*STUSER*); and (2) university expenditures on academic support per faculty member (*ACADSUP*).

The variables are presented in Table 1 along with their means and standard deviations. To most readers, it is cannot be surprising that graduation rates are lower at public compared to private universities; here public university graduation rates are more than ten percentage points lower. That lower rate is accompanied by an undergraduate enrollment that is approximately three times larger than private universities and a larger proportion of students that are low income grant recipients. However, public relative to private universities employ more than two and one half times the faculty along with a slightly larger faculty salary. Public university research grants and contract per faculty member are significantly greater than at private universities. The percent of tenured faculty at public universities is ten percentage points greater than at private universities, but private universities employ a greater percentage of non-tenure track faculty. Internal funding allocations indicate that private compared to public universities spend 150% more on student services but only 6.5% more on academic support.

Table 1. Private and public university variable means and deviations

| | Private | | Public | |
|---|---|---|---|---|
| Variable | Mean | Std. dev. | Mean | Std. dev. |
| *GRAD-RATE*, % | 56.96 | 13.03 | 43.42 | 13.51 |
| *UGR*, # | 2,700 | 1,876 | 8,591 | 5,524 |
| *LOWINC*, % | 28.62 | 13.89 | 34.41 | 15.45 |

Table 1 (cont.). Private and public university variable means and deviations

| | Private | | Public | |
|---|---|---|---|---|
| Variable | Mean | Std. dev. | Mean | Std. dev. |
| *GRD*, # | 1,080 | 1,151 | 1,572 | 1,499 |
| *FACULTY*, # | 135 | 82 | 335 | 185 |
| *SALARY*, $ | 61,241 | 10,707 | 63,437 | 9,974 |
| *RESCH*, $ | 20,448 | 32,122 | 201,488 | 72,366 |
| *TENURE*, % | 42.98 | 20.51 | 52.72 | 11.87 |
| *NTRACK*, % | 30.51 | 29.86 | 19.09 | 12.08 |
| *STUSER*, $ | 3,439 | 1,397 | 1,262 | 556 |
| *ACADSUP*,% | 8.96 | 3.56 | 8.41 | 2.93 |
| *N* (4 years) | 792 | 792 | 864 | 864 |

## 4. Results

Maximum likelihood estimates for the private and public university stochastic production frontiers are presented in Table 2. In both cases, the likelihood ratios are significant. Moreover, the estimate of gamma, the effect of inefficiency on the total error, is highly significant in both the public and private sectors, thereby supporting the notion that the stochastic frontier functional form is preferred over ordinary least squares without the inefficiency term. Among private universities, the positive and significant coefficient for *Eta* indicates that the private sector has become more efficient over time in producing undergraduate graduation rates. The reverse holds in the public sector with the evidence suggesting that university inefficiency has increased over four academic years.

Table 2. Frontier estimates for graduation rates

| | Private | | Public | |
|---|---|---|---|---|
| | Coefficient | *t*-value | Coefficient | *t*-value |
| Constant | 2.0577 | *3.0745 | 4.7534 | *7.7694 |
| *UGR* | -0.0116 | -0.4591 | 0.0403 | 0.8762 |
| *LOWINC* | -0.0728 | *-4.6479 | -0.1581 | *-7.0304 |
| *GRD* | -0.0275 | **-2.4737 | -0.0569 | *-3.0012 |
| *FACULTY* | 0.1422 | *5.8349 | 0.0987 | ***1.8493 |
| *SALARY* | 0.1762 | *2.5812 | 0.0929 | 1.5710 |
| *RESCH* | 0.0005 | 0.4578 | -0.1744 | *-5.7033 |
| *TENURE* | 0.0022 | ***1.6538 | 0.0439 | *3.6499 |
| *NTRACK* | -0.0001 | -0.0489 | 0.0035 | 1.2443 |
| *STUSER* | 0.0109 | 0.4681 | 0.0449 | 1.5601 |
| *ACADSUP* | 0.0165 | 0.8100 | -0.0682 | **-2.1796 |
| *Sigma ^2* | 0.2614 | *2.9888 | 0.1289 | *3.6238 |
| *Gamma* | 0.9662 | *78.3906 | 0.9072 | *36.1917 |
| *Mu* | -1.0052 | **-2.1796 | 0.2169 | ***1.7017 |
| *Eta* | 0.0356 | *3.0050 | -0.0127 | -1.2623 |
| Log likelihood | | 509.95 | | 374.53 |
| LL ratio | | *597.22 | | *750.36 |

Note: Significant at the 1%*, 5%**, and 10%*** level, respectively.

With respect to individual coefficients, the model performs quite well for both private and public university estimations. More than half of the coefficients reach statistical significance at the ten percent or better level. Surprisingly, the undergraduate student enrollment size (*UGRD*) effect carries the opposite sign in the two sectors but is statistically insignificant in both, i.e., undergraduate enrollment size appears to have no on graduation rates. That is not the case with respect to the proportion of undergraduate students enrolled that are recipients of low income grants. In both sectors, *LOWINC* has a statistically significant negative effect on the university graduation rates. A negative effect is also present with respect to graduate student enrollments (*GRD*). That suggests that an increased focus on graduate education comes at the expense of undergraduate success. However, it may be due to a greater presence of graduate teaching assistants in the undergraduate classrooms. More refined data would be needed to sort out the possible causes of the negative *GRD* effect.

In countering that negative effect, increased faculty employment (*FACULTY*) is estimated to improve university graduation rates within both university sectors. Increases in faculty salaries also produce positive graduation effects, but only significantly so in the somewhat lower paid private university sector.

Among public universities, graduation rates are estimated to decline with increased institutional research, i.e., *RESCH* is negative and statistically significant. Similar to the influences of graduate program enrollments (*GRD*), it is possible that an enhanced research emphasis funnels institutional attention away from undergraduate education and comes at the expense of graduation rates. That negative effect is not present among private universities where by the research measure employed in the analysis, university research is, on average, only 10% of what exists at public universities. Thus, the combined effects of *GRD* and *RESCH* suggest that within this same Carnegie classified group of universities, more specialized and undergraduate education focused universities produce higher graduation rates. That comes as little to no surprise but it is reassuring that the model specification empirically supports that a priori notion.

On the matter of faculty tenure, the results indicate that the tenure improves student graduation rates. The positive *TENURE* effect is statistically significant among both private and public universities: 10% level and better in the private sector and 1% level and better in the public sector. Non-tenure track faculty employment (*NTRACK*) opposite effects in the two sectors but is statistically insignificant in both. However, the negative *NTRACK* coefficient that emerged in the private sector can be of some concern, especially given that the average non-tenure track faculty employment in that sector is on the order of 30% of total faculty employment. The differences in sign effects between two sectors would be interesting to explore further with demographic data related to non-tenure track faculty.

For the final two explanatory variables, the results indicate that institutional expenditures on student services have insignificant effects on student graduation rates. But the student services measure that had to be employed is an aggregate expenditure. Obviously it would be preferable to have expenditure data related to specific types of services so that it would be possible to separate the effects of such things as technology services compared to health care services on graduation success. The same, of course, applies to the currently used measure of the *IPEDS* academic support services. Yet, given the negative effect of *ACADSUP* in the public sector, the estimates here suggest that public relative to private universities might be over spending on academic support services.

Table 3 presents the private and public university efficiency estimates from both the SFA and DEA models. For the DEA estimates both the CRS and VRS results are presented, although the CRS efficiencies are always lower due to the scale efficiency effects. Those scale efficiencies (i.e., CRS/VRS) can be derived for those interested but here they are approximately the same in both sectors.

Table 3. DEA and SFA university efficiency estimates

| | Private | | | Public | | |
|---|---|---|---|---|---|---|
| | CRS | VRS | SFA | CRS | VRS | SFA |
| Mean | 0.594 | 0.711 | 0.833 | 0.567 | 0.647 | 0.716 |
| Median | 0.618 | 0.787 | 0.859 | 0.597 | 0.732 | 0.733 |
| Min | 0.011 | 0.035 | 0.340 | 0.05 | 0.005 | 0.317 |
| Max | 1 | 1 | 0.982 | 0.200 | 1 | 0.984 |
| Std. dev. | 0.320 | 0.289 | 0.126 | 0.318 | 0.314 | 0.154 |
| Skew | -0.189 | -0.682 | -1.286 | -0.143 | -0.533 | -0.407 |
| Mean CRS & VRS distances and SFA efficiencies | | | | | | |
| 2005-06 | 0.597 | 0.715 | 0.826 | 0.569 | 0.668 | 0.720 |
| 2006-07 | 0.61 | 0.726 | 0.831 | 0.572 | 0.646 | 0.718 |
| 2007-08 | 0.584 | 0.717 | 0.836 | 0.565 | 0.642 | 0.715 |
| 2008-09 | 0.586 | 0.686 | 0.841 | 0.563 | 0.632 | 0.712 |

In Table 3, the primary DEA interest rests with the more general VRS model estimates and a comparison of those to the SFA efficiency estimates. In both sectors, the DEA-VRS efficiencies are lower than the SFA estimates. DEA does attribute deviations from the efficient frontier to inefficiency while SFA accounts for random variations in addition to inefficiency. While some studies have produced DEA efficiency estimates that are larger than SFA estimates (e.g., Wadud and White, 2000), the efficiencies differentials found here are similar to the findings presented in Theodoridis and Psychoudakis (2008) and the other supporting studies reviewed therein.

As indicated in Table 3, the DEA-VRS four year mean efficiency is 0.71 in the private sector and 0.65 in the public sector. The SFA estimated differences are 0.83 compared to 0.72 for the private vs. public university efficiency. When examined by academic year, the SFA efficiencies reveal the efficiency improvements attained among private universities and the efficiency degradation occurring in the public sector. Those changes are the monotonic inefficiencies corresponding to the *Eta* estimates in the SFA model. To see what underlies the Malmquist indices, the CRS and VRS mean distances are also presented. As indicated, there again inter-sector differences arise and, for example, VRS in the private sector shows one year of improvement but continuous declines in the public sector.

Across both models and sectors the distributions are negatively skewed. Also, the minimum university efficiency estimated under the VRS model is exceptionally low compared to the SFA minimum. Table 4 presents a clearer picture of the differences in the efficiency distributions.

Table 4. Efficiency distributions

| | Private | | | Public | | |
|---|---|---|---|---|---|---|
| Range | CRS | VRS | SFA | CRS | VRS | SFA |
| 0 | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| 0.1 | 7.1% | 2.0% | 0.0% | 9.3% | 7.4% | 0.0% |
| 0.2 | 9.1% | 6.6% | 0.0% | 7.4% | 6.0% | 0.0% |
| 0.3 | 5.6% | 4.5% | 0.0% | 11.1% | 6.0% | 0.0% |
| 0.4 | 10.6% | 5.1% | 1.0% | 7.4% | 6.5% | 3.2% |
| 0.5 | 8.1% | 6.1% | 1.5% | 8.8% | 5.6% | 7.4% |
| 0.6 | 7.6% | 9.1% | 3.5% | 6.0% | 6.5% | 12.0% |
| 0.7 | 10.6% | 7.6% | 6.1% | 8.3% | 9.7% | 20.8% |
| 0.8 | 8.1% | 11.6% | 20.2% | 10.6% | 10.6% | 21.8% |
| 0.9 | 6.1% | 8.6% | 31.8% | 12.0% | 13.9% | 22.2% |
| 1 | 27.3% | 38.9% | 35.9% | 19.0% | 27.8% | 12.5% |

Examining the upper end of the distributions presented in Table 4, the DEA-VRS model produces the largest percentage of universities estimated to have efficiency scores at 0.9 or better. Comparing the private to public efficiencies under the DEA-VRS model, there is about an 11% point difference in the 0.9-1.0 efficiency score frequencies (i.e., 38.9% vs. 27.8%) that favor the private universities in producing graduation rates. Under the SFA estimates, the difference expands to approximately 23% in favor of private university efficiency (35.9% vs. 12.5%). At the lower end of the efficiency distributions, the VRS estimation places approximately 24% of private universities at efficiencies below or at 50%. In the public sector, that percentage is approximately 32%. In contrast, the SFA model estimates that only

3% of private universities and 11% of public universities fall in the lower efficiency range.

Concluding the empirical investigation, the Malmquist productivity changes and decompositions are presented in Table 5. It shows the scale and pure or managerial efficiency change, technical efficiency change, technological change, and the resulting total productivity change. A brief examination of the private vs. public university results shows little opportunity for referencing any consistent pattern of changes. All the scale efficiency indices are above one in the public sector but fluctuate in the private sector. The pure or managerial efficiencies show little regularity over four academic years but there might be some concern associated with the 2008-09 academic year performance. That is, for both universities, there occurs a 2008-2009 deterioration in management efficiency. And in the private sector, that decline is just marginally offset by the scale efficiency changes so as to produce a 1.004 or 0.4% technical efficiency improvement.

In the public sector, however, the scale improvement is not powerful enough to counter the managerial decline and, therefore, the technical efficiency index remains below unity (but showing a slight advancement from 2007-2008 to 2008-2009).

Table 5. Malmquist total productivity estimates and decomposition indices

| | Private | | | | | Public | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *Scale* | *Mgt* | *Eff* | *Tech* | Total | *Scale* | *Mgt* | *Eff* | *Tech* | Total |
| 2006-07 | 1.012 | 1.024 | 1.036 | 0.734 | 0.761 | 1.044 | 0.958 | 1.000 | 0.736 | 0.736 |
| 2007-08 | 0.962 | 0.976 | 0.939 | 0.91 | 0.854 | 1.006 | 0.987 | 0.992 | 0.842 | 0.836 |
| 2008-09 | 1.072 | 0.936 | 1.004 | 0.906 | 0.909 | 1.021 | 0.975 | 0.995 | 0.888 | 0.883 |
| Mean | 1.014 | 0.978 | 0.992 | 0.846 | 0.839 | 1.023 | 0.973 | 0.996 | 0.819 | 0.816 |

The productivity decompositions do not support any claims to technological improvements in either sector's production of student graduation successes; all the technological change indices (*Tech*) are below unity. When that is combined with the poor showing on technical efficiency improvements, there can be little hope for overall gains in university productivity. In both sectors, the mean productivity index is below unity, thereby indicating productivity regress. Following Cooper et al. (2007), the public and private samples were combined and a rank-sum test was conducted to determine if, in this case, based on the productivities the two groups belong to the same population. For the total sample of 414 universities, the *t*-value for the test was 3.026 and, therefore, the hypothesis was rejected and it was concluded that they do not belong to the same population. That, of course, supports the earlier noted Chow test on the structural differences underlying the production technology that led to the initial separation of the two sectors. To the credit of both university sectors, however, the productivity indices as shown in Table 5 improve with each academic year and can, therefore, be interpreted as partial productivity progress. Some of that progress occurred during the global financial crisis and the negative budgetary impacts imposed upon both private and public universities. But interestingly, when evaluated over the four academic years, the mean productivity change (regress) is not substantially different (0.839 vs. 0.816) between two university sectors.

## Conclusions

This study provided empirical estimates of the operating efficiencies and productivity changes of the U.S. private and public universities in producing student educational success. The production of graduation rates and associated efficiencies were estimated using both SFA and DEA techniques. Panel data covered the 2005-2009 academic years and included over 400 Carnegie classified master's colleges and universities.

The importance of the study for public universities is based on the growing trend toward performance based financing with performance being, at least, partially tied to graduation rate successes. Unlike the public flagship and research universities, master's level universities will likely face greater competition for ever smaller pieces of the post-financial crisis funding appropriations. Moreover, there graduation outcomes are likely to be increasingly compared to their private higher education counterparts.

Under the SFA modeling presented in this paper, private relative to public universities were estimated to be of greater efficiency in graduating undergraduate students. Mean SFA efficiencies were approximately 83% in the private sector and 72% in the public sector. That, of course, is in accord with conventional wisdom in recognizing that public universities operate under a different mission and are chartered to serve the public in providing a wide net of educational access. On an academic year basis, the SFA results point to slight annual efficiency declines in the public sector, but only on the order of a total 1.1% over four years, but slight efficiency improvements among private universities, about 1.8% total over four years. The production frontier estimates that preceded the efficiency scores also generated some interesting results. For example, graduate program education was found to interfere and have negative impacts on undergraduate graduation rates. From a policy perspective, that implies that greater university specialization in undergraduate education could improve graduation rates. Reinforcement to that notion is the finding that increased university research activity negatively impacts undergraduate graduation success. But that finding was only present among public universities. Regarding faculty employment, increases in tenured faculty among the professorial ranks was found to have positive influences on university graduation rates.

Availability of panel data also provided the opportunity to explore university productivity changes using the Malmquist index and its associated decompositions. With respect to the latter, the findings show a recent pattern of decline in both private and public managerial efficiencies. The results also show an absence of overall improvement in technology. On average, both private and public universities were found to suffer productivity regress. The productivity decline was approximately the same in both sectors: 15% among private universities and 18% among publicly-owned universities. Encouragingly, however, improvements in the productivity indices with each passing academic year suggests that both university sectors have pruned away some of that regress and appear to be slowing moving toward the territory of productivity gains. That occurred during and following the global financial crisis. With that, both university sectors could be credited with warding off further productivity declines. How that plays out in future academic years will hopefully be explored as more data becomes available. That research will be of special importance for public universities if graduation efficiencies and productivities become critical measures for use in performance based financing.

In addition, future research could prove to be fruitful in comparing higher education to other industries in the U.S. and with universities in other countries – all with an eye toward investigating the possible efficiency and productivity changes possibly induced by the financial crisis and subsequent improvements or regress.

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