ACADEMIC R&D ACROSS THE STATES: EFFICIENCY AND ITS DETERMINANTS

Murat Arik, Middle Tennessee State University
Hulya Arik, Middle Tennessee State University
Bronwyn Graves, Middle Tennessee State University

ABSTRACT

A review of the literature suggests that there are few studies on the efficiency of academic research and development (R&D) funding in the United States. Much of the extant literature focuses on efficiency assessments at either the academic department level or the university level. We are not aware of any studies that analyze the efficiency of academic R&D funding at the state level. The purpose of this paper is to fill this void by assessing the efficiency of academic R&D funding at the state level using Data Envelopment Analysis (DEA), a non-parametric efficiency estimation method that can utilize multiple inputs and outputs to create a single efficiency score. The DEA results, along with results in changes in R&D productivity over time, suggest that some U.S. states are relatively better positioned to turn their R&D dollars into academic and business outputs. Tennessee is used as an example to show how to apply the DEA results to guide policy decisions toward efficiency. Tobit model results imply that the diversity of funding source, university R&D intensity, and R&D concentration are key for R&D funding efficiency. The policy implications of the study findings are discussed.

Keywords: Data envelopment analysis (DEA), research and development (R&D), academic efficiency, Tobit model

INTRODUCTION

Research and development (R&D) funding at universities provides the groundwork for increases in local business outputs and economic growth. Following the Arik and Ndrianasy (2018) conclusion that high levels of R&D funding on the state level often correlate with high state Gross Domestic Product (GDP) levels, and with the knowledge that R&D funding leads to business outputs, this paper investigates the efficiency with which universities utilize funding to create these growth-oriented outputs on the state level. This paper aims to create a model for estimating the technical efficiency and productivity growth of state-level R&D funding during the period 2006–2015. To this end, we created a Data Envelopment Analysis (DEA) model to determine efficiency, a Malmquist Index to calculate overall productivity increases, and a Tobit model using the DEA efficiency scores to uncover the determinants of efficiency.

The DEA model has been widely used since the early 2000s to evaluate the efficiency of multiple decision-making units (DMUs), from hotels to universities (Emrouznejad and Yang, 2018). The DEA model has many advantages, outlined in Section 2 below, but central to this paper is its ability to create an efficiency frontier from the data. This efficiency frontier is made up of efficient DMUs, as determined by the model, and can be used as a guide toward efficiency for

DMUs that are not on the efficiency frontier. The efficiency frontier, much like a production frontier, does not assume that one set of inputs and outputs is the best way to achieve efficiency; instead, it allows for many efficient combinations (Cooper et al., 2006).

In this paper, we created an output-oriented DEA model determining the efficiency of R&D funding to universities in creating business outputs. Different from what had been done in previous studies, we modeled R&D funding efficiency at the state level rather than at the academic department or university level. The state-level analysis provides new insights as it is the state economies, rather than universities themselves, that receive the benefits from the efficient transfer of R&D funding into business outputs, including startups and science and engineering graduate students. States, then, should be concerned about their universities' efficiencies as a whole and how they compare to other states with the goal of striving toward higher levels of efficiency. Our DEA model will serve to provide a new framework for R&D funding efficiency, and as we use a time frame of about ten years, historical comparisons and state comparisons will give decision makers new information about the efficiency of universities at the state level.

Additionally, though it has many sources, R&D funding comes primarily from private industry and the federal government (National Science Foundation). Any new insight into academic R&D efficiency will provide support for efficient states to prove that they can indeed turn increases in industry or federal R&D funding into business outputs. On the other hand, inefficient states apply a DEA model like the one provided below to determine how best to become efficient based on our DEA model's specified outputs.

With the knowledge that academic R&D plays a role in growing regional economies, the study of the logistics and efficiencies of R&D funding to universities will provide a foundation for understanding and improving the academic community's positive impact on the business community at the state level. Moreover, data on state-level R&D efficiencies can aid state- and federal-level decision makers as they determine which states receive federal R&D funding.

The paper is organized as follows. Section 2 discusses the background of DEA usage in various disciplines. Section 3 describes the methodology and research questions used by the models for efficiency estimates, productivity changes, and Tobit regression. The results are presented in Section 4. In Section 5, implications and limitations are discussed. Section 6 concludes the paper.

BACKGROUND

Academic R&D Overview

Academic R&D is an important determinant of GDP growth at the state level (Arik and Ndrianasy, 2018). Although total dollar amounts spent on academic R&D are important, whether the states use those academic research dollars efficiently has not received enough attention in the literature. As laid out in Table 1, Federal University R&D spending in the U.S. was around $37.9 billion in 2015, representing about 0.21 percent of the U.S. GDP, a decline from 0.25 percent in 2010. Because a significant amount of taxpayer dollars is invested in the process, an examination of the issue at the state-level rather than the university-level has important public policy implications.

Table 1: Federal University R&D

	2010	2015
Total University R&D	$61.2 billion	$68.7 billion
Total Federal University R&D	$37.5 billion	$37.9 billion
Federal University R&D as a percent of the U.S. GDP	0.25%	0.21%

Source: Authors, BEA, and National Science Foundation

DEA Literature Review

Data Envelopment Analysis (DEA) modeling is widely used to measure the relative efficiency of decision-making units (DMUs). Over the years, the number of published studies using DEA as a method of analysis has grown dramatically, as shown in Figure 1 below. The recent trend suggests that the top five heavily-focused topical areas are agriculture, banking, supply chain, transportation, and public policy (Emrouznejad and Yang, 2018).

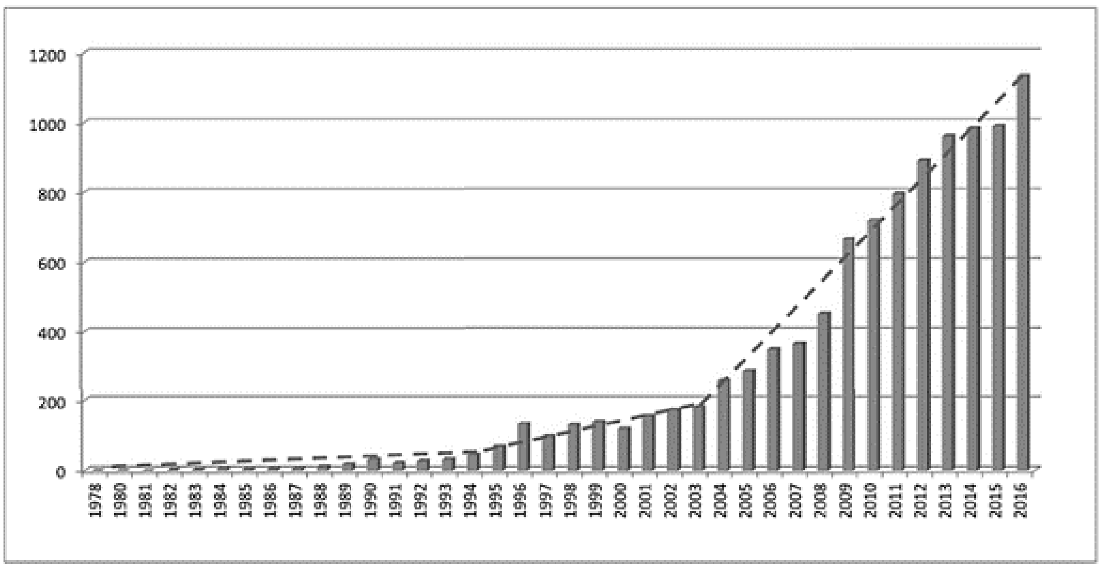

Fig. 1: Distribution of DEA-related articles by year (1978–2016). Source: Emrouznejad and Yang (2018)

A careful review of the titles of approximately 11,000 articles related to DEA reveals that a small fraction (83) of those articles deals strictly with either R&D efficiency in general or university-related efficiency measures. Among those 83 articles, only a handful are directly related to academic R&D at the state level. Table 2 breaks down the types of R&D efficiency-related DEA articles.

Table 2: R&D Efficiency-Related DEA Articles

Unit of Analysis	Number of Articles
Country	10
Country/Industry	13
Country/University	17
University-Department	4
General R&D	13
Industry R&D	13
International R&D Comparison	3
University Efficiency	10
Total	83

Source: Author's Review

DEA is a non-parametric mathematical procedure used to measure and assess the efficiency of a DMU, such as a firm or a university, when compared to other DMUs in the same category. DEA uses input and output ratio data for the DMUs to construct relative efficiency scores for all DMUs and from those scores creates an efficiency frontier. Efficiency scores range from zero (0) to one (1), with one (1) marking efficiency and all other scores marking inefficiency. DMUs on the efficiency frontier have a score of one (1), and efficient DMUs become the “benchmark” peers for the inefficient DMUs. For each inefficient DMU, based on its input-output data, at least one efficient peer DMU is calculated. That peer can be a guide toward efficiency, for example, by showing that an increase in a particular output would be the best choice. The goal of using DEA is to provide data that will show inefficient DMUs how to perform more efficiently with their available resources (Cooper et al., 2006).

“DEA has two primary advantages: It does not require a specification of either the production function form or the weights of different inputs and outputs, and it provides detailed information on the efficiency of the unit relative to specific efficient units as comparators” (Chen et al., 2011). Variations on the DEA model structure have been made, including those that re-evaluate efficient DMUs to determine if inputs can be even further decreased (Zhu, 2001) and those that use hierarchal methods to evaluate better the input-output combinations themselves (Inoue et al., 2015). DEA is widely used in areas such as manufacturing, banking, education, health care, management evaluation, and commerce.

In a broader application, DEA can be used to evaluate data in fuzzy environments. Fuzzy set theory is a method to quantify imprecise and vague data in DEA models. When compared with fuzzy linear programming, the efficiencies of DEA proved the better measurement for quantifying fuzzy data. The subsequent results of this comparison introduced the possibility for using a new α-level based approach and a numerical method for ranking DMUs with fuzzy data (Raeinojehdehi and Valami, 2016). In a fuzzy environment, different decision makers have different attitudes toward which inputs they want to evaluate. The significance of using a fuzzy number is that the decision-makers can make decisions based on their own preferences and in real-world situations. DEA evaluations make it possible for decision-makers to use the information they select (Chen and Wang, 2016; Liu, 2011).

DEA has been successfully used in many studies in the following ways:

Industry

In the travel industry, DEA has been used to evaluate the efficiency of hotels (Lei and Liu, 2018), airliners (Pisarek and Zoltaszek, 2016), and cruise ships (Demirer et al., 2017). A common finding in these studies is that increasing the size of the DMU often does *not* translate to increased efficiency.

In health care, nonprofits such as the Red Cross, large health care systems, and individual hospitals have been evaluated using DEA to determine inefficiencies (Rauner and Sommersguter-Reichmann, 2015; Abeney and Yu, 2015; Chen et al., 2011). In the insurance industry, DEA provided insight into microinsurance, showing that due to the wide variety of program performance, a comprehensive "best practice" benchmark is needed (Biener and Eling, 2011).

In the banking and finance industries, DEA has been used to determine institutional efficiencies in banking in Nigeria (Avinde, 2017), to help managers monitor exchange and interest rates (Zakaria, 2017), and to show that the overall efficiency scores of IPO firms are dismal (Anjum and Sohail, 2016).

Despite their complexity, DEA has also been used to pinpoint inefficiencies in supply chains (Chern and Chou, 2016) and to determine efficiencies in areas lacking research attention, such as sports sponsorships (Bijmolt et al., 2016). DEA has been validated as an appropriate method for "identify[ing] efficient discrete-event simulation software" (Lall and Moreno, 2011) and has even been used to formulate a new method for calculating the human development index (Eren et al., 2017).

Academic Institutions

DEA has the ability to rank overall measure of quality, an important measure for higher education, and the DEA method has been validated in many papers as suitable for the assessment of higher education institutions (Bougnol and Dulá, 2006; Johnes, 2006). In many studies and in various countries, DEA is used to determine the efficiency scores of academic institutions with multiple specifications. Among country-level studies are those in South Africa (Taylor and Harris, 2004), the Czech Republic (Mikusova, 2015), England (Bradley et al., 2010; Thanassoulis et al., 2011), Canada (Datta and McMillan, 1998), Turkey (Bursalioglu and Selim, 2013), France (Barros et al., 2011), and Europe as a region (Veiderpass and Mckelvey, 2016).

Some additional applications of DEA in institutions of higher education include determining "best buy" universities (Eff et al., 2012), "improving estimates of per-student education costs" (Salerno, 2006), evaluating a country's "perceived" top universities and liberal arts colleges (Breu and Raab, 1994; Eckles, 2010), evaluating a country's top business schools (Palocsay and Wood, 2014), and determining efficiencies of specific academic departments (Cimpoies et al., 2016; Dogan et al., 2014; Duguleana and Duguleana, 2015). A common theme among these studies is providing a scientific method for ranking institutions rather than relying solely on subjective or survey rankings.

Academic R&D

In addition to DEA studies that focus on higher education institutions themselves, DEA has also been used to determine the efficiency of those institutions' outputs, namely R&D outputs. DEA has been verified as an appropriate tool for quantifying research efficiency in academia, identifying benchmarks, and contrasting research efficiency with other traditional rankings (Korhonen et al., 2011; Munoz, 2016). As with studies of academic institutions, DEA-based academic R&D efficiency analyses involve many specifications. Among country-level studies published are a Taiwanese study of team communication and its relevance to academic R&D efficiency (Hung et al., 2013), several Chinese investigations into general research performance (Chuanyi et al., 2016; Johnes and Yu, 2008; Ng and Li, 2000), a study of "efficiency and technological change" for U.S. universities (Barham et al., 2011), and one in Malaysia examining measures for "knowledge management performance" (Kuah and Wong, 2013).

Other regional or multi-country studies have been realized as researchers attempt to uncover different facets of academic R&D efficiency by changing the scope of their analysis. These include studies of a single Italian region (Agasisti et al., 2011), of incoming European Union (EU) member states (Aristovnik, 2012), and of the higher education systems of the Organization for Economic Co-operation and Development (OECD) countries (Bayenet and Debande, 1999). In the same way, the current study aims to provide information on U.S. state-level academic R&D efficiency, a facet that has not yet been given intense research attention.

Research and Development (R&D)

In fields and institutions heavily involved in R&D activities, evaluating the outputs of R&D funding is crucial. As is the case for academic R&D, DEA has been used frequently to evaluate the efficiency of non-academic R&D institutions as well, on many levels and with various goals. DEA has been broadly proven to be a suitable method for evaluating R&D activities across multiple research subjects (Dilts et al., 2015; Lee et al., 2011; Li et al., 2014; Sengupta, 1999; Sharma and Thomas, 2008; Wang and Huang, 2007). National R&D investment efficiency and effectiveness have been evaluated using DEA (Jiménez-Sáez et al., 2011; Lee et al., 2009; Shi and Yang, 2008). As R&D is often funded wholly or in part by government agencies, the need to assess the efficient use of public funds has led to many DEA-based studies on government-subsidized R&D efficiency (Hsu and Hsueh, 2009; Lee and Lee, 2015; Park, 2015). Additionally, how the efficiencies of both parties are affected by the partnership between the public and private R&D sectors has been studied using DEA (Revilla et al., 2007). DEA has also been used to create "guidelines" for R&D policy-makers by addressing the question: "Who leads productivity growth?" (Jiménez-Sáez et al., 2013).

DEA has been used in many regional- and provincial-level studies to determine R&D efficiency, such as those looking at regional investments (Zhong et al., 2011), the "transformation of knowledge-based economies" (Afzal and Lawrey, 2014), regional technical efficiency (Bergantino et al., 2013), and "production frontier performance" at the province level (Guan and Chen, 2010). R&D efficiency has been examined using DEA on the institutional level as well, in a study of "scope economies" at U.S. research universities (Chavas et al., 2012) and a study of the growth involved with scientific R&D institutes in China (Meng and Wang, 2014).

R&D efficiency has been evaluated on the industry level using DEA in such industries as pharmaceuticals (Hashimoto and Haneda, 2008), information technology (Sueyoshi and Goto, 2013), and manufacturing (Dočekalová and Bočková, 2013). DEA has been used to evaluate the "returns to growth" for technology-based firms "facing hyper-competition" (Sahoo et al., 2011). DEA has similarly played a part in determining efficiencies in agricultural research on the country-level (Gomes et al., 2011; Hartwich and von Oppen, 2006), within a single region (Rehber and Tipi, 2006), and between firms (Oztop and Ucak, 2017). DEA has been used to determine the impact of barriers to entry on R&D efficiency (Cullmann et al., 2012) and to solve "target-setting difficulties" through "technology forecasting" (Anderson et al., 2012). DEA has likewise been applied to determine the efficiency of networks in "evaluating the R&D linking efficiency of innovation ecosystems" (Chen and Hung, 2016).

As shown by these and other previous studies, DEA calculations are useful in identifying efficiencies that can affect the performance of an organization. These efficiency findings can reveal potential areas of improvement that decision-makers can use to reduce risk and better their organization. The current analysis uses DEA to determine state-level efficiency of academic R&D funding in providing desirable business outputs.

METHODOLOGY

Research Questions

Federal funding represents a large portion of total funding for R&D at government and academic institutions alike. Academic institutions that receive federal funding for R&D programs are often closely examined to determine their ability to produce desired outputs. In this study, we follow this vein of the investigation, with the additional emphasis on whether R&D at academic institutions on the state-level is *efficient* in creating the desired outputs.

Research Question 1: *Are states efficient in converting taxpayer dollars into business outputs?*

Next, we further look into the historical state-level academic R&D efficiency levels and their components to discover whether and how they have changed.

Research Question 2: *How has the productivity of academic R&D at the state level changed over time?*

Lastly, we delve into the environmental factors that contribute to R&D efficiencies and attempt to learn whether those states with efficient academic R&D share similar environmental characteristics.

Research Question 3: *What are the determinants of the efficiency of academic R&D?*

Efficiency Estimates

To determine whether states are efficient in converting taxpayer dollars into business outputs, we use an output-oriented DEA model to create efficiency estimates. We use the model below, as specified by Cooper et al. (2006):

$$\begin{aligned} &\mathrm{Max}_{\emptyset,\lambda}\ \emptyset, \\ &\mathrm{st} \quad -\emptyset y_i + Y\lambda \geq 0, \\ &\qquad x_i - X\lambda \geq 0, \\ &\qquad \mathrm{N1}'\lambda = 1 \\ &\qquad \lambda \geq \theta, \end{aligned}$$

To estimate the maximum efficiency of R&D, represented by $\mathrm{Max}_{\emptyset,\lambda}\, \emptyset$,, the output-oriented, variable returns to scale (VRS) model is used where 1≤Ø≤∞ and Ø-1 indicate the proportional increase in outputs that could be achieved for the i-th firm with input quantities held constant. The output-oriented nature of the model tests to what level inputs y can be reduced without changing the quantity of outputs x. Yλ and Xλ represent the efficiency reference set for the corresponding variables. The constraint, N1'λ=1, accounts for differences in whether or not firms are operating at an optimal scale. The projected point of each institution can then be benchmarked against others, where the DEA frontier is a convex combination rather than a linear one. Thus, the output-oriented model offers insight into the measurement of technical inefficiency as a proportional increase in output production for firms with a fixed quantity of resources. This provides for an accurate evaluation of relative efficiency that takes into account both technical and scale efficiencies.

Productivity Change

To observe changes in state-level academic R&D productivity over time, we use an output-based Malmquist Index and decompose the overall total factor productivity (TFP) results into categories such as scale efficiency and technical efficiency as in Orea (2002).

$$m_o(y_{t+1}, x_{t+1}, y_t, x_t) = \left[\frac{d_o^t(x_{t+1}, y_{t+1})}{d_o^t(y_t, x_t)} \times \frac{d_o^{t+1}(x_{t+1}, y_{t+1})}{d_o^{t+1}(y_t, x_t)}\right]^{1/2}$$

The output-based Malmquist TFP Index measure was used to determine the productivity change index when *x* and *y*, again, represent outputs and inputs, respectively. The model represents the productivity of the production point (x_{t+1}, y_{t+1}) relative to the production point (y_t, x_t). A value greater than one (1) indicates positive TFP growth from period *t* to period *t*+1. The index is the geometric mean of two output-based Malmquist TFP indices. One of these indexes uses period *t* technology and the other period *t*+1 technology. This is determined based on the four linear programming problems that calculate each of the component distance functions; $d_o^t(x_{t+1}, y_{t+1})$, $d_o^t(y_t, x_t)$, $d_o^{t+1}(x_{t+1}, y_{t+1})$, $d_o^{t+1}(y_t, x_t)$. Each linear programming equation was calculated for each DMU for every time period measured.

Tobit Model

To address any environmental factors that could affect the efficiency of a firm, we used Stata software to run a second stage Tobit regression. This captures the effects of influences from environmental factors such as R&D intensity, state-level GDP, or the state's R&D-related startups. Unlike a traditional OLS regression model, the Tobit model, or censored regression model, estimates linear relationships between variables with left- or right- censoring in the dependent variable and is able to account for truncated data. It also served to identify and counteract any biases resulting from our first methodological step, the DEA model, which gives an efficiency score that is both left- and right-censored (bounded between zero (0) and one (1)). In this stage, the efficiency scores from the first analysis are regressed on the chosen environmental variables. The signs of the coefficients of these variables indicate the direction of the influences. The Tobit model then uses the regression's estimated coefficients and their random errors to adjust efficiency scores for censor-based bias. This helps to address both continuous and categorical variables affecting the outcomes of the efficiency tests.

Data

Data comes from the Association of University Technology Managers (AUTM) surveys, the National Science Foundation (NSF), the Bureau of Economic Analysis (BEA), and the National Center for Educational Statistics (NCES).

The DEA model's two input variables are (1) real university R&D (in 2009 dollars) and (2) total faculty and science and engineering (S&E) research staff (in number of persons). The seven output variables are (1) total patents, (2) total licenses, (3) total startups, (4) doctorate degrees, (5) master's degrees, (6) S&E graduate students, and (7) S&E postdocs. Table 3 reports the correlations between the DEA model variables. Though the variables exhibit signs of strong correlations, the DEA model's nonparametric specification alleviates estimation bias due to multicollinearity, unlike the bias seen in linear models (Akazili et al., 2008).

Table 3: Correlations Between Model Variables

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Output									
[1] All Patents (AUTM)	1								
[2] Licenses Issued (AUTM)	0.63	1							
[3] Startups Formed (AUTM)	0.87	0.84	1						
[4] Doctorate Degrees (NCES)	0.78	0.81	0.94	1					
[5] Master's Degrees (NCES)	0.75	0.80	0.92	0.98	1				
[6] S&E Grad Students (NCES)	0.85	0.76	0.95	0.97	0.95	1			
[7] S&E Postdocs (NCES)	0.84	0.76	0.92	0.85	0.84	0.89	1		
Input									
[8] Total R&D University Expenditures (2009)	0.84	0.80	0.95	0.93	0.92	0.97	0.92	1	
[9] Faculty and SE Non-Faculty Research Staff	0.80	0.80	0.94	0.97	0.95	0.98	0.85	0.96	1

Estimation Method

This study used Multi-stage Data Envelopment Analysis (DEA), Malmquist Productivity Index, and Tobit Model to estimate (a) relative efficiency of each state; (b) changes in efficiency measures by state; (c) projected (target) output values to reach efficiency level; (d) peer state DMUs for Tennessee, as an example; (e) productivity change over the years studies; and (f) determinants of relative efficiency.

This study utilized an output-oriented approach: given the input level, how much of an increase in outputs can be made to increase efficiency.

RESULTS

Efficiency Results

Table 4: Key Terms

Output-oriented model	This model is used to test whether a decision-making unit (DMU) can increase its output while keeping the input fixed
Constant Returns to Scale (CRS)	Changes in inputs and outputs are proportional
Variable Returns to Scale (VRS)	Production technology may be increasing, constant, or decreasing in terms of returns to scale
Technical Efficiency (TE)-Constant Returns to Scale (CRS)	Ability of a DMU to get the maximum output given the input levels under the VRS technology
Technical Efficiency (TE)-Variable Returns to Scale (CRS)	Ability of a DMU to get the maximum output given the input levels under the CRS technology
Scale Efficiency (TE-CRS/TE-VRS)	The component of technical efficiency associated with the scale of operation

Table 4 provides definitions for the key terms used in the DEA output tables. For purposes of this paper, the relative efficiency score used is the variable returns to scale technical efficiency (TE-VRS). This category is shaded in Table 5, which shows the states ranked by TE-VRS score for the years 2006, 2009, 2011, and 2015. These years were chosen for the study to account for the impact of the 2007-2009 major recession, where the year 2006 represents “before,” the year 2009 represents “during,” and the year 2011 represents “after.” The year 2015 is included as it was the last year the data were available.

Table 5 provides annual efficiency scores of all states in the four years covered in this study. In 2006, as seen on the table, only 12 states in the U.S. were operating efficiently in terms of maximizing the academic outputs given the amount of R&D spending and academic employment (shown by the box around all TE-VRS that equal one (1)). As has been mentioned, technical efficiency that allows variable returns to scale (VRS) is the measure of pure efficiency. A score of one (1) is deemed efficient, and any score of less than one (1) is efficiency-deficient. The rankings indicate how a state compares to the rest in terms of pure efficiency. Interestingly, efficient states show constant or increasing returns to scale. The inefficient states (except Georgia and Wisconsin) show decreasing returns. For example, Tennessee (in bold) ranked 28th in terms of pure efficiency and shows decreasing returns to scale.

The 2009 column of Table 5 shows that in that year 15 states were operating efficiently in terms of maximizing the academic outputs given the amount of R&D spending and academic employment. Though the number of the efficient states increased from 2006, more efficient states showed decreasing returns to scale in 2009 than in 2006. Given the efficiency scores shown in Table 5, we can see that states often maintain their place in the ranking over time, usually only moving a few places up or down. For example, Tennessee ranked 28th in pure efficiency in 2006 and moved to 31st in 2009. South Carolina is an example of a large decrease in efficiency, moving from 25th in 2006 to 38th in 2009. Studying the efficiency scores for a longer time frame would shed more light onto the patterns of change in state R&D efficiency.

Table 5: Annual Efficiency Scores, 2006-2015

2006

State	TE (CRS)	TE (VRS)	Rank (VRS)	SE	Return to Scale
CA	1.000	1.000	1	1.000	-
FL	1.000	1.000	1	1.000	-
IL	1.000	1.000	1	1.000	-
MA	1.000	1.000	1	1.000	-
MI	1.000	1.000	1	1.000	-
NC	0.834	1.000	1	0.834	irs
NE	0.355	1.000	1	0.355	irs
NJ	1.000	1.000	1	1.000	-
NY	1.000	1.000	1	1.000	-
OH	1.000	1.000	1	1.000	-
VA	1.000	1.000	1	1.000	-
WA	1.000	1.000	1	1.000	-
TX	0.905	0.959	13	0.943	drs
PA	0.833	0.955	14	0.872	drs
GA	0.726	0.877	15	0.828	irs
WI	0.765	0.870	16	0.879	irs
AZ	0.015	0.465	17	0.032	drs
UT	0.035	0.419	18	0.083	drs
MD	0.367	0.418	19	0.876	drs
IA	0.031	0.389	20	0.079	drs
MN	0.023	0.346	21	0.068	drs
IN	0.020	0.298	22	0.067	drs
MO	0.011	0.292	23	0.036	drs
CO	0.028	0.266	24	0.106	drs
SC	0.050	0.260	25	0.192	drs
CT	0.062	0.251	26	0.246	drs
OR	0.039	0.251	26	0.156	drs
TN	**0.053**	**0.246**	**28**	**0.217**	**drs**
DC	0.014	0.232	29	0.060	drs
ID	0.044	0.188	30	0.234	drs
AL	0.019	0.161	31	0.116	drs
NM	0.045	0.158	32	0.286	drs
LA	0.008	0.148	33	0.052	drs
ND	0.024	0.127	34	0.186	drs
KY	0.010	0.126	35	0.082	drs
KS	0.007	0.107	36	0.065	drs
OK	0.005	0.106	37	0.049	drs
HI	0.019	0.085	38	0.225	drs
MT	0.005	0.077	39	0.064	drs
MS	0.005	0.068	40	0.068	drs
DE	0.065	0.066	41	0.997	-
NH	0.010	0.063	42	0.153	drs
AR	0.003	0.055	43	0.049	drs
WV	0.003	0.050	44	0.067	drs
RI	0.002	0.043	45	0.039	drs
NV	0.004	0.040	46	0.094	drs
VT	0.007	0.038	47	0.180	drs
ME	0.003	0.026	48	0.129	drs
SD	0.012	0.024	49	0.481	drs
AK	0.001	0.014	50	0.061	drs
Average	0.309	0.431		0.412	

2009

State	TE (CRS)	TE (VRS)	Rank (VRS)	SE	Return to Scale
AZ	0.220	1.000	1	0.220	drs
CA	1.000	1.000	1	1.000	-
CO	0.936	1.000	1	0.936	irs
FL	1.000	1.000	1	1.000	-
IL	1.000	1.000	1	1.000	-
IN	1.000	1.000	1	1.000	-
MA	1.000	1.000	1	1.000	-
MD	0.756	1.000	1	0.756	drs
MI	1.000	1.000	1	1.000	-
MO	1.000	1.000	1	1.000	-
NY	0.901	1.000	1	0.901	drs
OH	1.000	1.000	1	1.000	-
TX	0.786	1.000	1	0.786	drs
VA	1.000	1.000	1	1.000	-
WA	1.000	1.000	1	1.000	-
PA	0.796	0.977	16	0.814	drs
GA	0.830	0.960	17	0.865	irs
NC	0.723	0.925	18	0.781	drs
WI	0.638	0.778	19	0.819	irs
UT	0.022	0.393	21	0.055	drs
MN	0.016	0.328	22	0.049	drs
NJ	0.016	0.314	23	0.050	drs
KY	0.018	0.289	24	0.062	drs
OR	0.014	0.253	25	0.054	drs
IA	0.009	0.235	26	0.038	drs
VT	0.090	0.229	27	0.392	drs
DC	0.007	0.214	28	0.034	drs
ND	0.007	0.214	28	0.034	drs
NV	0.096	0.212	30	0.455	drs
TN	**0.005**	**0.206**	**31**	**0.023**	**drs**
AL	0.004	0.172	32	0.024	drs
CT	0.010	0.154	33	0.068	drs
AR	0.006	0.136	34	0.041	drs
LA	0.003	0.135	35	0.025	drs
NM	0.008	0.114	36	0.067	drs
KS	0.009	0.111	37	0.084	drs
OK	0.003	0.098	38	0.029	drs
SC	0.004	0.098	38	0.045	drs
NE	0.003	0.083	40	0.040	drs
MS	0.002	0.068	41	0.030	drs
ME	0.004	0.067	42	0.054	drs
WV	0.003	0.065	43	0.052	drs
MT	0.002	0.055	44	0.036	drs
NH	0.008	0.050	45	0.166	drs
ID	0.007	0.046	46	0.151	drs
RI	0.005	0.046	46	0.105	drs
HI	0.004	0.045	48	0.089	drs
SD	0.003	0.045	48	0.062	drs
DE	0.002	0.036	50	0.056	drs
AK	0.001	0.016	51	0.057	drs
Average	0.340	0.463		0.388	

2011

State	TE (CRS)	TE (VRS)	Rank (VRS)	SE	Return to Scale
CA	1.000	1.000	1	1.000	-
CO	0.880	1.000	1	0.880	irs
FL	1.000	1.000	1	1.000	-
GA	0.989	1.000	1	0.989	irs
IL	1.000	1.000	1	1.000	-
MA	1.000	1.000	1	1.000	-
MO	1.000	1.000	1	1.000	-
NJ	1.000	1.000	1	1.000	-
NV	0.829	1.000	1	0.829	irs
NY	1.000	1.000	1	1.000	-
PA	1.000	1.000	1	1.000	-
TX	0.886	1.000	1	0.886	drs
VA	1.000	1.000	1	1.000	-
WA	1.000	1.000	1	1.000	-
IN	0.827	0.972	15	0.850	irs
AZ	0.872	0.904	16	0.965	irs
MI	0.884	0.887	17	0.996	irs
OH	0.834	0.844	18	0.988	drs
NC	0.772	0.779	19	0.991	drs
WI	0.673	0.760	20	0.886	irs
MD	0.562	0.563	21	0.998	irs
MN	0.082	0.359	22	0.229	drs
UT	0.065	0.313	23	0.209	drs
OR	0.077	0.309	24	0.250	drs
AL	0.143	0.252	25	0.569	drs
CT	0.118	0.243	26	0.487	drs
DC	0.125	0.237	27	0.528	drs
IA	0.120	0.213	28	0.561	drs
ND	0.046	0.206	29	0.224	drs
TN	**0.049**	**0.183**	**30**	**0.266**	**drs**
KS	0.169	0.174	31	0.973	drs
LA	0.032	0.139	32	0.234	drs
VT	0.127	0.129	33	0.986	irs
ID	0.107	0.122	34	0.880	drs
KY	0.022	0.121	35	0.180	drs
ME	0.038	0.113	36	0.339	drs
OK	0.017	0.096	37	0.180	drs
SC	0.022	0.095	38	0.233	drs
MS	0.050	0.089	39	0.555	drs
AR	0.081	0.087	40	0.939	drs
NE	0.019	0.086	41	0.225	drs
WV	0.013	0.084	42	0.149	drs
NM	0.015	0.072	43	0.206	drs
MT	0.029	0.060	44	0.474	drs
RI	0.024	0.051	45	0.475	drs
NH	0.017	0.050	46	0.346	drs
HI	0.028	0.046	47	0.601	drs
DE	0.021	0.039	48	0.555	drs
SD	0.006	0.023	49	0.284	drs
AK	0.004	0.018	50	0.217	drs
Average	0.414	0.474		0.652	

2015

State	TE (CRS)	TE (VRS)	Rank (VRS)	SE	Return to Scale
CA	1.000	1.000	1	1.000	-
CO	0.964	1.000	1	0.964	irs
CT	0.603	1.000	1	0.603	irs
FL	1.000	1.000	1	1.000	-
IL	1.000	1.000	1	1.000	-
IN	1.000	1.000	1	1.000	-
MA	1.000	1.000	1	1.000	-
MI	1.000	1.000	1	1.000	-
NJ	1.000	1.000	1	1.000	-
NY	0.934	1.000	1	0.934	drs
OH	1.000	1.000	1	1.000	-
PA	1.000	1.000	1	1.000	-
TX	0.827	1.000	1	0.827	drs
VA	1.000	1.000	1	1.000	-
WA	1.000	1.000	1	1.000	-
GA	0.873	0.956	16	0.913	irs
NC	0.706	0.758	17	0.931	drs
MN	0.075	0.717	18	0.105	drs
WI	0.633	0.703	19	0.900	irs
AZ	0.145	0.579	20	0.250	drs
OR	0.133	0.528	21	0.252	drs
MD	0.463	0.496	22	0.934	drs
MO	0.068	0.372	23	0.182	drs
TN	**0.356**	**0.362**	**24**	**0.984**	**drs**
NH	0.032	0.301	25	0.106	drs
UT	0.086	0.287	26	0.298	drs
IA	0.021	0.265	27	0.081	drs
ME	0.057	0.227	28	0.253	drs
DC	0.028	0.185	29	0.150	drs
KY	0.035	0.174	30	0.204	drs
AL	0.025	0.173	31	0.146	drs
ND	0.022	0.161	32	0.134	drs
WV	0.071	0.158	33	0.448	drs
LA	0.019	0.142	34	0.136	drs
NE	0.039	0.131	35	0.297	drs
KS	0.020	0.120	36	0.163	drs
ID	0.034	0.108	37	0.315	drs
SC	0.020	0.106	38	0.186	drs
NM	0.018	0.095	39	0.193	drs
OK	0.014	0.092	40	0.150	drs
AR	0.014	0.080	41	0.169	drs
MS	0.014	0.078	42	0.176	drs
RI	0.045	0.076	43	0.593	drs
NV	0.019	0.066	44	0.287	drs
DE	0.017	0.063	45	0.277	drs
MT	0.009	0.046	46	0.200	drs
VT	0.012	0.038	47	0.316	drs
HI	0.008	0.035	48	0.237	drs
SD	0.004	0.027	49	0.145	drs
AK	0.004	0.019	50	0.233	drs
Average	0.369	0.474		0.513	

Note: TE (CRS) stands for technical efficiency with constant returns to scale, TE (VRS) stannds for technical efficiency with variable returns to scale, and SE stands for scale efficiency

For returns to scale: irs= increasing returns to scale
drs= decreasing returns to scale
- = constant returns to scale

In 2011, 14 states were operating efficiently in terms of maximizing the academic outputs given the amount of R&D spending and academic employment, though the number of efficient states with increasing and constant returns to scale returned to what it had been in 2006. More non-efficient states showed increasing returns to scale as well. The increasing returns to scale showed that inefficient states seemed to be striving toward efficiency. Again, overall states moved only slightly in terms of pure efficiency ranking. For example, Tennessee ranked 30th for pure efficiency in 2011 (28th in 2006 and 31st in 2009).

In 2015, 15 states were operating efficiently in terms of maximizing the academic outputs given the amount of R&D spending and academic employment, and fewer of the non-efficient states had increasing returns to scale compared to 2011. Tennessee ranked 24th in terms of pure efficiency.

The DEA state-level R&D efficiency scores for the four years presented above show that states which comprise the efficiency frontier have generally remained efficient throughout the years of this study. This result is not surprising. It makes sense that it is more likely for an efficient state to remain efficient over a few years' time than for an inefficient state to become efficient in the same amount of time.

Tennessee and Neighboring States as a Case Study

Examining the historical scores of geographical neighbors can be another way for states to benchmark and measure their R&D efficiency as characteristics of universities show geographical clustering. In this case study, we used Tennessee and its neighboring states as an example. Tennessee's scores and its peers' scores are detailed in Table 6. Among Tennessee's neighboring states, Florida, North Carolina, Virginia, and Georgia have scored consistently either on or near the efficiency frontier in the years of the study, while Tennessee's efficiency scores have been consistently below the 50-state average. This suggests that these neighboring states' universities have some sort of institutional advantage over the universities in Tennessee, whether this be the number of R&D-focused institutions or the intensity of the R&D focus in those institutions. By this comparison, one can see that Tennessee ranks in the middle of this Southeast state cluster. However, geography might not be the best criterion for comparison, as the ranks and efficiency scores fail to delve into the reasons for state efficiency. To find more appropriate comparisons, we return to the DEA model.

Table 6: Academic R&D Efficiency: Tennessee vs. Its neighbors

	2006		2009		2011		2015	
	TE-CRS	TE-VRS	TE-CRS	TE-VRS	TE-CRS	TE-VRS	TE-CRS	TE-VRS
Florida	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Virginia	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
North Carolina	0.834	1.000	0.723	0.925	0.772	0.779	0.706	0.758
Georgia	0.726	0.877	0.830	0.960	0.989	1.000	0.873	0.956
South Carolina	0.050	0.260	0.004	0.098	0.022	0.095	0.020	0.106
Tennessee	**0.053**	**0.246**	**0.005**	**0.206**	**0.049**	**0.183**	**0.356**	**0.362**
Alabama	0.019	0.161	0.004	0.172	0.143	0.252	0.025	0.173
Kentucky	0.010	0.126	0.018	0.289	0.022	0.121	0.035	0.174
Mississippi	0.005	0.068	0.002	0.068	0.050	0.089	0.014	0.078
Average	0.309	0.431	0.340	0.463	0.414	0.474	0.369	0.474

Note: States are sorted from highest TE-VRS in 2006 to lowest. TE-CRS is Technical Efficiency-Constant Returns to Scale; TE-VRS is Technical Efficiency-Variable Returns to Scale.

The DEA model itself formulates a unique set of efficient "peer" states for each inefficient state. These peer states provide information about options to achieve efficiency for the inefficient states. The DEA model accomplishes this through "slacks." The slacks are model-determined variables that, when changed, could result in the state becoming efficient. Using the slack information in combination with the input-output ratios for each state, the model matches an inefficient state with peers, those that have a similar input-output structure.

The DEA model creates slacks to show what variables a state could change to become efficient. For Tennessee to be efficient given the level of academic R&D input and staff for 2015, it may be able to increase S&E postdocs, S&E graduate students, and patents. Table 7 shows the original value and the slacks for Tennessee's outputs. For example, in 2015, the state had large output slacks in patents, meaning that these are the outputs that are leading to Tennessee's inefficiency.

Table 7: Academic R&D Efficiency: What It woud take for Tennessee to be efficient?

	2006		2009		2011		2015	
Output	Original Value	Slacks	Original Value	Slacks	Original Value	Slacks	Original Value	Slacks
[1] All Patents (AUTM)	669	2,468	647	11,467	969	14,827	1,009	1,087
[2] Licenses Issued (AUTM)	86	0	80	0	74	15	122	39
[3] Startups Formed (AUTM)	8	19	3	57	0	0	14	20
[4] Doctorate Degrees (NCES)	2,354	0	2,503	1,174	2,989	0	3,679	0
[5] Master's Degrees (NCES)	9,047	4,182	10,144	0	11,099	6,357	11,839	3,951
[6] S&E Grad Students (NCES)	8,051	5,535	8,075	19,415	8,167	21,000	8,204	7,509
[7] S&E Postdocs (NCES)	763	2,752	801	4,990	1,098	1,824	909	119

Peers are determined by the DEA model as the efficient states that have input-output ratios which best fit a target state's original and slack values. Based on the 2015 efficiency assessment, Pennsylvania and California are Tennessee's aspirational peers in terms of the input-output ratios. In Table 8, notice that the slacks for each of these efficient peer states are zero (0), meaning the model can find no way for them to improve. The DEA model assumes that there exist more than one path to attain efficiency; instead, the model creates a "frontier" of efficiency possibilities.

Table 8: Academic R&D Efficiency for Tennessee and Its Peers (2015)

	Tennessee		Pennsylvania		California	
Output	Original Value	Slacks	Original Value	Slacks	Original Value	Slacks
[1] All Patents (AUTM)	1,009	1,087	3,825	0	40,196	0
[2] Licenses Issued (AUTM)	122	39	376	0	464	0
[3] Startups Formed (AUTM)	14	20	59	0	149	0
[4] Doctorate Degrees (NCES)	3,679	0	10,158	0	18,296	0
[5] Master's Degrees (NCES)	11,839	3,951	36,628	0	70,761	0
[6] S&E Grad Students (NCES)	8,204	7,509	30,111	0	83,680	0
[7] S&E Postdocs (NCES)	909	119	2,620	0	10,601	0
Input						
[8] Total R&D University Expenditures (2009)	959,057,450		3,056,045,054		7,767,003,691	
[9] Faculty and SE Non-Faculty Research Staff	12770		32521		63186	

This efficiency frontier is similar to a production possibilities frontier. A production frontier shows the combination of production outputs that are possible for a firm given inputs and costs, while the output-oriented efficiency frontier shows the different combinations of outputs that can be considered efficient. It follows, therefore, that one state could have more patents and fewer startups than another efficient state while still being on the "frontier" of efficiency.

Productivity Change

Following the Malmquist Index methodology outlined previously, we created two tables breaking down the efficiency (or productivity) change over time. The first table (Table 9) shows averages of productivity changes between the time periods used in the present study as well as the separated factors of the total changes. The second table (Table 10) shows state averages for productivity changes over the entire span from 2006 to 2015.

Overall, since 2006, states experienced the greatest change in efficiency in the period 2009-2011, as shown in Table 9. This efficiency change was driven by a large increase in scale efficiency. Increasing returns to scale was highlighted previously in the discussion of the DEA output for 2011. Additionally, pure technical efficiency was on the increase in all three periods.

Table 9: Malmquist Index Summary of Annual Means

Year	Efficiency Change (Effch)	Technical Efficiency Change (Techch)	Pure Technical Efficiency Change (Pech)	Scale Efficiency Change (Sech)	Total Factor Productivity Change (Tfpch)
2006/2009	0.789	**1.379**	**1.073**	0.735	**1.087**
2009/2011	**3.536**	0.293	**1.045**	**3.385**	**1.036**
2011/2015	0.706	**1.523**	**1.028**	0.686	**1.075**
Average	**1.253**	0.850	**1.049**	**1.195**	**1.066**

Note: Efficiency change larger than 1 (e>1) = increasing productivity, Efficiency change less than 1 (e<1) = decreasing productivity, Efficiency change equal to 1 (e=1) = no change in productivity

Technical and scale efficiency seem to be opposite in terms of increasing and decreasing productivity, meaning that when technical efficiency increases in productivity, scale efficiency decreases in productivity.

Examining changes in efficiency provides a case for encouraging productivity growth even in states that are not efficient. These results provide a clearer insight into states' efficient use of R&D funding. For example, in the DEA results above, Tennessee's ranking varies from 24th to 31st in the nation in terms of R&D efficiency. However, by the Malmquist Index results shown in Table 9, Tennessee ranks 6th among U.S. states in terms of productivity gains between 2006 and 2015. In Table 10, shaded cells represent efficiency scores of one (1) or above. Therefore, while Tennessee is average among the states in terms of institutional R&D efficiency, its productivity changes show the state is indeed above average among the states in improving efficiency.

Table 10: Malmquist Productivty Index: Summary of State Averages (2006-2015)

State	Efficiency Change (Effch)	Technical Efficiency Change (Techch)	Pure Technical Efficiency Change (Pech)	Scale Efficiency Change (Sech)	Total Factor Productivity Change (Tfpch)	Tfpch Rank	State	Efficiency Change (Effch)	Technical Efficiency Change (Techch)	Pure Technical Efficiency Change (Pech)	Scale Efficiency Change (Sech)	Total Factor Productivity Change (Tfpch)	Tfpch Rank
AK	1.732	0.653	1.105	1.568	1.131	19	MS	1.437	0.726	1.047	1.372	1.043	25
AL	1.105	0.696	1.023	1.081	0.769	43	MT	1.226	0.981	0.841	1.458	1.203	15
AR	1.711	0.756	1.134	1.509	1.294	11	NC	0.946	0.967	0.912	1.038	0.915	38
AZ	2.140	0.658	1.075	1.990	1.409	9	ND	0.972	0.965	1.084	0.897	0.939	35
CA	1.000	1.058	1.000	1.000	1.058	22	NE	0.479	0.817	0.508	0.942	0.391	50
CO	3.240	1.031	1.554	2.085	3.339	2	NH	1.494	0.775	1.686	0.886	1.157	17
CT	2.136	0.674	1.586	1.347	1.440	8	NJ	1.000	0.912	1.000	1.000	0.912	39
DC	1.261	0.695	0.927	1.360	0.876	40	NM	0.740	0.867	0.843	0.878	0.642	45
DE	0.643	0.719	0.985	0.653	0.462	49	NV	1.723	0.687	1.187	1.451	1.183	16
FL	1.000	1.051	1.000	1.000	1.051	23	NY	0.977	0.949	1.000	0.977	0.927	37
GA	1.064	1.056	1.029	1.033	1.123	20	OH	1.000	1.069	1.000	1.000	1.069	21
HI	0.759	0.819	0.746	1.017	0.621	47	OK	1.388	0.733	0.955	1.454	1.018	26
IA	0.886	0.918	0.880	1.007	0.813	42	OR	1.502	0.863	1.281	1.173	1.296	10
ID	0.918	0.694	0.831	1.105	0.637	46	PA	1.063	1.181	1.015	1.047	1.256	12
IL	1.000	0.999	1.000	1.000	0.999	27	RI	3.010	0.669	1.211	2.485	2.014	4
IN	3.695	1.044	1.498	2.467	3.859	1	SC	0.734	0.918	0.742	0.989	0.674	44
KS	1.413	0.691	1.040	1.359	0.977	32	SD	0.695	0.708	1.037	0.670	0.492	48
KY	1.509	0.754	1.113	1.355	1.137	18	**TN**	**1.884**	**0.906**	**1.138**	**1.656**	**1.707**	**6**
LA	1.362	0.730	0.986	1.381	0.994	28	TX	0.971	1.015	1.014	0.957	0.985	31
MA	1.000	0.987	1.000	1.000	0.987	30	UT	1.350	0.908	0.882	1.531	1.226	13
MD	1.081	0.862	1.058	1.022	0.932	36	VA	1.000	0.970	1.000	1.000	0.970	33
ME	2.578	0.840	2.060	1.251	2.165	3	VT	1.204	0.698	0.999	1.205	0.841	41
MI	1.000	0.994	1.000	1.000	0.994	28	WA	1.000	1.051	1.000	1.000	1.051	23
MN	1.477	0.826	1.276	1.158	1.220	14	WI	0.939	1.010	0.931	1.008	0.948	34
MO	1.860	0.880	1.084	1.715	1.637	7	WV	2.761	0.685	1.468	1.881	1.892	5
							Average	1.253	0.850	1.049	1.195	1.066	

Note: Efficiency change larger than 1 (e>1) = increasing productivity, Efficiency change less than 1 (e<1) = decreasing productivity, Efficiency change equal to 1 (e=1) = no change in productivity

When comparing Tennessee to its neighboring efficient states, one can see that Florida, Georgia, North Carolina, and Virginia all rank at or below 20 in terms of increases in productivity change. In general, for the information presented in Table 10, states that are efficient lack large increases in productivity when compared to the nation. However, the opposite does not hold true: inefficient states do not consistently show large increases in productivity over time. Mississippi, South Carolina, and Kentucky—Tennessee's non-efficient neighboring states—all rank at or below 18 in terms of productivity. In the Tennessee example, one can see that, though inefficient, Tennessee outranks its neighbors, both the efficient and non-efficient states, in terms of productivity changes. These comparisons imply that Tennessee is making strides toward academic R&D efficiency, though it remains in the category of non-efficient.

Determinants of Efficiency

To understand the determinants of the efficiency scores of the states, we used a Tobit random effect panel model for the years 2006, 2009, 2011, and 2015. The dependent variable is the relative efficiency value extracted from the DEA analysis above. The model is both right- and left-censored, as dependent variable values are bounded between zero (0) and one (1). At least four Tobit model variations were tested. Dependent and independent variables are listed in Table 11.

We chose independent variables for determining efficiency through two assumptions: one is that efficiency is determined by the existing institutional and state environment and the other is that the type or distribution characteristics of the R&D funding can influence efficiency. The environmental variables are the number of Faculty and S&E Non-Faculty Research Staff, number of R&D-related startup companies, and State Gross Domestic Product per capita. We expect these variables to be high when efficiency is high, as the higher levels of these variables imply that R&D funding would be high and that business outputs would be more efficiently produced.

Table 11: Tobit Model Variables Used

Dependent	
Efficiency	State DEA efficiency score, $0 \leq$ efficiency ≤ 1
Independent	
FSENFRS	Number of Faculty and S&E Non-Faculty Research Staff
STARTUPS	Number of R&D-related start-up companies
GDPPC	State Gross Domestic Product per capita
RDINTEN	R&D Intensity measured as All Academic R&D/Total GDP
RDDIV	R&D Diversity, measured by sources of academic R&D (industry, federal, state, and federal research institute)
CONIDIV	Interaction term between concentration and diversity
RDINSDIV	R&D Institutional diversity
RDINSD2	R&D Intensity, squared
RDCONC2	R&D State Concentration, squared
RDCONC	R&D State Concentration
RDDIV2	R&D Diversity, squared

For funding, we defined four characteristics: concentration, diversity, institutional diversity, and intensity. Concentration measures a state’s ratio of federal funding compared to the national federal funding ratio. Diversity measures R&D funding source diversity (e.g., federal, state, and institutional sources). Institutional diversity measures the number of institutions that receive R&D funding in a state. Intensity measures a state’s academic R&D funding as a share of the state GDP. We expected concentration and intensity to correlate positively with efficiency. Funding diversity was expected to correlate negatively with efficiency, as different sources of funding (government or industry) might seek different outcomes for their funds and these differences could cause inefficiency when, for example, multiple entities are funding the same program or department. We also expected institutional diversity to correlate negatively with efficiency according to the assumption that a single institution receiving more funds would likely produce a greater number of outputs than multiple institutions receiving much lesser amounts of funding.

The independent variables include the number of faculty and science and engineering non-faculty research staff per million dollars of R&D funding (FSENFRS), the number of R&D-related startup companies per million dollars of R&D funding (Startups), and state gross domestic product per capita (GDPPC). The other independent variables, described below, have to do with measures and indices of intensity, diversity, and concentration of R&D funding.

R&D intensity is measured as a state's total academic R&D funding normalized by the state's GDP (RDINTEN). Diversity has two meanings and measures in this model. The first is R&D source funding diversity, which measures how many different sources contribute to a state's R&D funding, such as federal or institutional sources (RDDIV). This funding source diversity is set up as a diversity index, as described by Arik and Livingston (2014):

$$RDDIV = 1 - \sum S_u^2,$$

where RDDIV represents the sum of state-level funding diversity, and S(u) represents each source's fraction of a university's R&D funding. By this equation, if a university has a single source of funding—source gives 1.0 (or 100 percent) of funding—its score will be zero (0), so scores closer to zero (0) imply low diversity and scores closer to one (1) imply high diversity.

The second diversity variable measures the institutional diversity of R&D funding in a state (RDINSDIV). This shows the share of the total state R&D funding received by a university or institution. Barring notation, the formula is the same as the diversity formula above:

$$RDINSDIV = 1 - \sum F_u^2,$$

where RDINSDIV is the state-level sum of institutional shares of a state's R&D funding, and F(u) represents the fraction of funding received by a given university. If a single university receives all R&D funding in a state—1.0 (or 100 percent) of funding—the state's score will be zero (0). Scores close to zero (0) indicate low diversity, while scores close to one (1) indicate high diversity.

R&D concentration (RDCONC) is measured using a location quotient, where the relative concentration of academic R&D funding in a state is compared with the relative academic R&D funding in the entire United States.

$$RDCONC = \frac{FFRD_{STATE} / TRD_{STATE}}{FFRD_{US} / TRD_{US}},$$

where $FFRD_{STATE}$ is the federally-funded R&D in a state, TRD_{STATE} is the total R&D in a state, $FFRD_{US}$ is the total federally-funding R&D in the U.S., and TRD_{US} is the total R&D funding in the U.S. If RDCONC is less than one (1), the state's ratio is less than the national ratio. If RDCONC is greater than one (1), the state's ratio is greater than the national ratio and that the state receives a proportionally greater amount of federal funding than do other states. The closer RDCONC is to one (1), the closer the state is to the national ratio of federal to total R&D funding.

This concentration measure of federal funding is important since, after the Bayh-Dole Act of 1980, universities that receive federal funding can take out licenses and patents on the research discoveries they make (Arik and Ndrianasy, 2018).

The final independent variable is an interaction term between R&D concentration and funding source diversity. The equation is simply:

$$CONIDIV = RDDIV * RDCONC,$$

where CONIDIV is the interaction term, RDDIV is source diversity, and RDCONC is a state's R&D concentration relative to the U.S.

We tested four models, and model results are presented in Table 12. Results significant at the 99 percent significance level are outlined in bold.

Table 12: Tobit Random Effect Panel Data Assessment: Determinants of Relative Efficiency

Efficiency	(1)	(2)	(3)	(4)
Constant	0.6840**	0.2530	-0.4210	-0.5014
	0.2694	***0.2287***	***0.3649***	***0.3246***
FSENFRS	-0.0137	-0.0096	-0.0074	-0.0065
	0.0078	***0.0065***	***0.0064***	***0.0061***
STARTUPS	4.6189***	4.4711**	3.5707	3.7123***
	2.5007	***2.2655***	***2.2176***	***2.1983***
RDINTEN	-2.7636	-7.5909**	-5.8188***	-5.6658***
	3.4170	***3.1676***	***3.1359***	***3.1250***
GDPPC			0.000	
			0.000	
RDDIV	0.0770	0.2248	3.7798**	3.8853*
	0.3197	***0.2839***	***1.2408***	***1.2232***
RDCONC		40.5011*	46.9816*	46.8982*
		9.2187	***9.1633***	***9.1465***
CONIDIV	26.3367*	-13.6122	-19.9494***	-19.4538***
	6.5468	***11.1604***	***10.9909***	***10.933***
RDINSDIV	-1.2488***	-0.8231	-0.821	-0.7785
	0.6973	***0.5748***	***0.5483***	***0.541***
RDDIV2			-4.5334**	-4.6464**
			1.5262	***1.5102***
RDINSD2	1.0352***	1.0032***	1.0115***	0.9643***
	0.6268	***0.5446***	***0.5238***	***0.5143***
RDCONC2	-67.5186	-81.4838*	-81.3011*	-82.7077*
	87.1010	***16.8192***	***16.3791***	***16.1359***
Sigma u	0.2274	0.1488	0.1315	0.1311
Sigma e	0.2236	0.2272	0.2247	0.2251
Rho	0.5083	0.3002	0.255	0.2535
Predicted*Observed Efficiency	0.6856	0.8048	0.8147	0.8139
r^2	0.47	0.6477	0.6637	0.6624

Note: Robust standard errors are reported in bold and italics.

*,**,*** indicate significance at 99%, 95%, and 90% levels, respectively

Sigma u and *sigma e* represent the panel-level and overall variance of the model, respectively. All four models had *sigma u* and *sigma e* variances with p-values at the 99 percent significance level. Additionally, the coefficients' signs remain the same across all models, with the exception of CONIDIV, which was positive in the first model and subsequently negative for the last three models.

Model 1 has a correlation of 0.6856 between its predicted values and the observed values. The only 0.05-level significant determinant of efficiency is CONIDIV, which is the interaction term between the concentration ratio of R&D funding and the diversity of the source of R&D funding. The relationship between efficiency and CONIDIV is positive. FSENFRS, RDINTEN, RDINSDIV, and RDCONC2 all correlate negatively with efficiency. Startups, RDDIV, and RDINSD2 positively correlate with efficiency. This implies that faculty and staff, R&D intensity, institutional diversity, or squared concentration correlate with a decrease in efficiency. Increases in startups, R&D diversity or squared institutional diversity would correlate with an increase in efficiency.

Model 2 adds a non-squared R&D concentration term (RDCONC). This addition increases the correlation to 0.8048, with the added term significant at the 0.05 level. Startups, RDINTEN, and RDCONC2 also are significant at the 0.05 level. Startups positively correlate with efficiency, meaning that the more startups there are in a state, the more efficiently the state is able to use university R&D to produce business outputs. RDINTEN, measuring R&D intensity, negatively correlates with efficiency. This means that as the ratio of academic R&D to total (state) GDP goes up, efficiency decreases. RDCONC correlates positively with efficiency, but RDCONC2 correlates negatively with it.

After the concentration variable is added, the models' correlation between the predicted and the observed values hover around 0.81. In Model 3 there is added a squared version of the R&D diversity score (RDDIV2) and a variable for GDP per capita (GDPPC). At 0.8147, this model has, of all the models tested, predicted values that correlate best with the observed values. In this model, RDDIV, RDDIV2, RDCONC, and RDCONC2 are all significant at the 0.05 level or lower. RDINSD2 is significant at the 0.053 level, and thus will be counted as significant. As seen in Model 2, the concentration variable follows the same correlation pattern, where RDCONC is positively correlated, and RDCONC2 is negatively correlated. The normal and squared terms for R&D funding diversity follow the same pattern. The R&D intensity and its square also have opposite signs, where RDINTEN is negatively correlated, and RDINSD2 is positively correlated. This means that in cases of R&D intensity, while intensity negatively correlates with efficiency, there might be a point that increasing intensity does lead to higher levels of efficiency. However, RDINTEN is not significant at the 0.05 level, and thus there can be no strong conclusion drawn.

Model 4 has the next best correlation of 0.8139. Model 4 is the same as Model 3 except for the removal of the variable GDPPC. Without the insignificant variable GDPPC, IDINSD2 is not significant, but the startups variable becomes significant at the 0.10 level. Additionally, RDDIV becomes significant at the 0.01 level. The other significant variables have the same signs and remain as significant as in Model 3.

The addition of a squared term for many of the significant variables suggests levels of the variables that optimize the efficiency score for R&D funding. This is especially true because, for these variables with significant squared terms, the squared term correlates with efficiency in the opposite direction from the non-squared term (e.g., RDCONC correlates positively, and RDCONC2 correlates negatively). This implies that the concentration of R&D funding has a positive effect on efficiency. However, as the concentration increases the effect of concentration on efficiency is lessened.

Across the models tested, those variables we identified as "environmental" variables were not significant or barely significant in one or two models. In the model with the best R-square, none of the environmental variables were consistently significant. This suggests that environmental effects could be captured by other unknown variables.

STUDY IMPLICATIONS, LIMITATIONS AND FUTURE RESEARCH

This analysis of academic R&D funding efficiency suggests that only about 30 percent of states may be considered relatively efficient. When analyzed historically, the same states consistently operated at the efficiency frontier.

Study Implications

Since a significant portion of academic R&D is financed by the taxpayers, a state by state efficiency analysis may provide better insights for policymakers to make responsible choices. Efficiency scores alone, however, do not provide the full picture, as many efficient states remain efficient over time. A more comprehensive understanding comes from examining total factor productivity as it relates to R&D funding efficiency and its changes on the state level. Together, these provide state policymakers with the basis to make a case for increases in their states' portion of federal funding or, in some instances, to make the case to an industry that the investment in a state's universities will lead to increased business outputs in that state.

The key determinants of relative efficiency are diversity, intensity, and concentration variables. These variables all relate to the type and distribution of R&D funding; none of the environmental variables we tested proved consistently significant. This implies that those who provide the funding have an impact on the efficiency of the funding, as funding diversity and funding concentration are directly under the control of the funding decision-makers. R&D intensity and R&D institutional diversity are, similarly, variables over which the DMU (the state) has little control. This means that states should be doing all they can to make their universities attractive to funding entities, namely the federal government and private industry.

Study Limitations and Improvements

One of the limitations of the current study was in the outputs of the DEA model. Though empirically supported by a previous study (Arik and Ndrianasy, 2018), the business outputs used in creating the efficiency scores were hardly all-inclusive. There may be different factors that support local economies, but that were not captured in this study. Furthermore, economies often improve due to factors that are difficult to measure. Thus academic R&D could have effects on local economies that have not yet been measured.

One of the major potential improvements to the study is covering a longer time frame. This would shed more light on the efficiency status of states, as we noted that a ten-year time frame might not reveal incremental increases in efficiency. Increasing the number of years analyzed would allow us to construct a more clear pattern of efficiency and would allow us to consider whether the first-mover advantage is important in efficiency, i.e., once a state achieves efficiency, how likely is it to stay efficient?

Another potential improvement to the study would be to include different environmental factors in the Tobit regression for efficiency determinants. The variable for startups proved minimally significant, and the variable for science and engineering faculty was never significant. In other words, we have not yet found the variables that capture the environmental impact on R&D efficiency, if indeed they exist.

Future Research

In order to expand beyond the bounded DEA efficiency score, a DEA model based on "super efficiency" could give a fuller picture of the states on the efficiency frontier (Zhu, 2001). With the DEA model used in this paper, efficient states are not provided any "decision points," while inefficient states are provided, through slacks created by the model, more than one means by which to increase efficiency.

CONCLUSION

States vary in how much R&D funding they receive and in the amount of business outputs they produce. Our output-oriented data envelopment analysis model uses input-output ratios of state-level university data to create an efficiency frontier. DEA efficiency tables from 2006, 2009, 2011, and 2015 show the changes in state efficiency and highlight that over time the same states remain on the efficiency frontier. Our Tennessee example demonstrates the efficient peers and slacks that are determined by the model to provide directions toward efficiency. In Tennessee's case, the state could seek to increase S&E post docs, S&E graduates, and patents.

Our Malmquist Index breaks the increases in total factor productivity into four types of productivity—efficiency change, technical efficiency change, pure technical efficiency, and scale efficiency—in order to show which type drove increases in TFP over the years 2006 to 2015. We find that the 2009 to 2011 period had the largest scale efficiency and the smallest technical efficiency. We show that state-level TFP measures can serve as evidence for states that want to demonstrate that their academic R&D efficiency is improving even if they are not operating on the efficiency frontier.

The Tobit regression of determinants of efficiency highlights the importance of federal R&D funding ratio (RDCONC), R&D source diversity, and R&D intensity in a state. The environmental factors tested were lowly significant or not significant. This implies that universities can produce business outputs efficiently even in states lacking large numbers of R&D-related startups or high GDP levels. These results also suggest that funding decision- makers (federal government or industry groups) play a role in the efficiency of state-level academic R&D through the variables of concentration and funding diversity.

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