Is government funding critical to the operating performance of technology universities? A case study of Taiwan

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Abstract

This study utilizes the Malmquist Productivity Index (MPI) to evaluate the operating performance of technology universities in Taiwan. The bootstrap method is employed to analyze MPI sensitivity to verify the index's stability. Our results suggest that the universities demonstrate an adequate level of performance with little improvement required. Technology universities with a greater proportion of total income from government subsidies did not evidence better operating performance. We argue that how universities obtain their funding is critical. Our findings will help universities (and their relevant departments) improve performance and better allocate resources.

Keywords Education · Malmquist Productivity Index · Bootstrap method · Technology universities · Productivity · Taiwan

JEL classifications D24 · H5 · L89

Introduction

The technology-concentrated manufacturing industry is the foundation of the Taiwanese economy, and technology education is the foundation of its manufacturing industry. Taiwan is a leading country in many technological sector and ranks first worldwide in terms of market share in custom integrated sector, chlorella and high-end-bicycles and number two in many more sectors. The country is betting on technology and science innovation to drive its growth and therefore, it invests in funding academic research in universities more particularly in science and technology to continue to drive the innovation and maintain the country global competitive position. Although Taiwan has a high population density, it has few natural resources, and is capable of sustaining its economic development miracle because of its abundant and highly productive labor force.

Thus, technological and vocational education is vital (Kang & Lee, 2009; Tian & Hsu, 2004; Yung & Hsu, 2006) and the operating performance of technology universities cultivating technology personnel will affect Taiwan's economic development.

Taiwan's technology and vocational education system comprises vocational high schools, vocational colleges, technology colleges, and technology universities. Different from general universities, the educational objective of technology universities is to cultivate practical and applied capacity, and to obtain school-industry collaboration. The latter is needed to cultivate technology and managerial personnel required by industry to enhance industrial and national competitiveness (Clark, 1998; Ministry of Education, 2011; Reich, 1991; Schaafsma, 1996; Taylor, 2001).

Technology universities in Taiwan are either national or private. National technology universities are established and owned by the government for cultivating advanced engineering and technology personnel in order to meet the demand of fast economic and industrial development. Private technology universities are established with assistance from industries through fundraising, in order to cultivate industrial technology personnel. Companies also fund and establish schools for cultivating their own labor.

Given the importance of the Taiwan's technology sector and thereby technology universities, our paper will investigate

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operating performance of technology universities based on funding sources. Specifically, we will examine the resource conversion of technology universities with higher/lower government subsidies to ascertain if government subsidizing policies significantly impact operating performance. Rather than assuming that government funding automatically helps, this study contributes to the literature by investigating the relative efficiency of technology universities with higher/lower government funding. Despite of the importance of these universities, to the best of our knowledge no other studies were conducted on the efficiency of technology universities following the recent reforms.

Data envelopment analysis (DEA) has been used to evaluate the operating performance of university education (Abbott & Doucouliagos, 2003; Alabdulmenem, 2017; Avkiran, 2001; Kao & Hung, 2008; Shamohammadi & Oh, 2019; Tran & Villano, 2018). However, DEA cannot be used to analyze intertemporal efficiency. Thus, we use the Malmquist Productivity Index (MPI), a DEA extension proposed by Färe et al. (1994). However, the MPI is problematically associated with unknown efficiency allocation, non-randomization, and a lack of statistical inference, which renders statistical inference difficult. Thus, to overcome these problems, we also used the bootstrap method (Efron, 1979) for data re-sampling.

Our results can help governments decide when and how to allocate educational resources. An additional second objective of our paper is to investigate efficiency change, technical change, and MPI change in the operating performance of Taiwan's technology universities. Population allocation inference was conducted to assist administrative units in decision-making and resource allocation. We also contribute to the literature by examining the effect of intellectual capital on university performance. Specifically, we incorporate a two-stage approach, whereby we continue with a regression analysis after efficiency analysis. Examining environmental factors reveal more detailed aspects on the determinants of university performance.

This remainder of this paper is organized as follows. Section 2 reviews the literature on performance studies of universities. Section 3 introduces the study design. Section 4 presents the empirical analysis. Section 5 discusses management implications. Section 6 discusses the study's limitations and offers policy suggestions.

Literature review

Development of technological and vocational education in Taiwan

Taiwan has 3-year academic and vocational upper secondary schools as well as some comprehensive schools offering programs in both areas. As of 2020, 5% of students attended comprehensive schools with the rest equally divided between the academic and vocational schools. In addition to upper secondary schools, there is also a 5-year junior college option that offers more specialized programs, leading to an associate degree, typically in technical areas. After upper secondary school, students from both academic and vocational schools can either take an entrance exam for university, or a technical and vocational college entrance exam to study at junior colleges, technical colleges, or universities of science and technology.

Taiwan's government attaches great importance to technological and vocational education (TVE), given the strong ties between TVE and economic development. The government began to press forward economic development plans in the 1950s, starting with sweeping improvements in agricultural production technologies, and actively developing labor-intensive essential goods industries. At that time TVE's primary role was providing agriculture-related and business-related programs at vocational schools. The focus was on training people with entry-level technical workplace skills needed for the country's growing economic development. In the 1960s, Taiwan's economy entered a period of export expansion. Small and medium enterprises flourished with a great demand for skilled workers for both industry and business. This led to fewer students attending agricultural vocational schools and a substantial increase in students at industrial and commercial vocational schools.
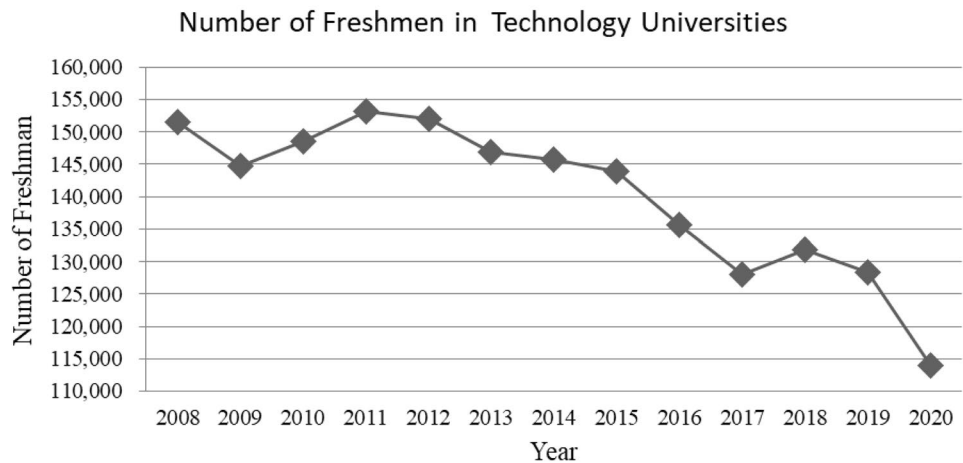
Taiwan began implementing 9-year compulsory education in 1968. Junior vocational schools were abolished but the number of vocational schools at the senior secondary level rapidly expanded. To meet the needs of industry, the Ministry of Education also encouraged establishing private vocational schools and private junior college level education, to provide an adequate mid-level skilled labor force for Taiwan's economic transformation. In the 1970s, the transition of traditional industries into capital and technology-intensive industries began, accompanied by an ongoing demand for an expanded workforce with increasingly high-quality skills. To further improve the quality of post-secondary TVE, the Ministry of Education established its Department of Technological and Vocational Education in 1973, and the National Taiwan Institute of Technology, Taiwan's first institute of technology was established in 1974. This was the beginning of the current comprehensive TVE sequence, which starts with a vocational high school followed by a junior college then an institute of technology. In the 1980s, the government gradually increased the ratio between the number of students undertaking senior secondary vocational education and the students at general senior high schools, reaching its goal of 7:3. The vocational high schools (all at the

Table 1 2007–2010 University budget structure

		Incomes from basic technology learning tuition fees (%)	Technology diffusion and school-industry collaboration incomes (%)	Life-long learning and on-job continue education incomes (%)	Government subsidy (%)	Group or private donation (%)	Other (%)	Total (%)
2007	Public	20.84	20.37	1.42	50.01	0.82	6.54	100
	Private	65.31	6.66	2.85	11.29	3.92	9.97	100
2008	Public	20.91	21.23	1.37	49.25	0.69	6.55	100
	Private	65.71	7.07	2.91	10.84	2.36	11.11	100
2009	Public	19.69	20.81	1.29	51.6	0.97	5.64	100
	Private	65.45	7.9	2.84	12.43	1.93	9.45	100
2010	Public	19.46	22.01	1.26	50.6	0.74	5.93	100
	Private	66.06	9.02	2.96	11.27	2.72	7.97	100

Source: The Study on the budget structure and the efficiency in colleges. Ministry of Education Taiwan. Retrieved from https://www.edu.tw/default.aspx

Fig. 1 Number of freshmen in technology universities. Source: Monthly bulletin of statistics of the ministry of the interior (2021). Retrieved from: https://ws.moi.gov.tw/001/Upload/400/relfile/0/4413/79c158fd-d51f-4061-b24b-fbcdb0fb92d9/month/month.html

senior secondary level) trained large numbers of workers, enabling Taiwan's economy to grow rapidly.

In the mid-1980s, Taiwan's economic development confronted challenges from internationalization and the open market, and the demand for workers with higher level technological and vocational skills increased dramatically. In response, in 1996 the government encouraged junior colleges to change their institutional status and become institutes of technology; and encouraged outstanding institutes of technology to rename themselves as universities of science and technology to facilitate training highly skilled people to meet the needs of industry (Ministry of Education of Taiwan, 2019).

According to the budgetary revenue structure, the preponderant income of national universities is government subsidies, followed by technology diffusion and school-industry collaboration income, and the incomes from basic technology learning tuition fees. The financial source of private universities is mainly tuition and fees, followed by government subsidies (Table 1).

Figure 1 displays the number of freshmen entering universities per year. Enrollment increased from 2009 to 2011 followed by a downward trend.

Figure 2 illustrates the annual number of births. It decreased from 2008 to 2010, then increased between 2010 and 2012, and has since decreased. The drop in birth may explain the downward trend in university enrollment.

DEA for education organization performance evaluation

Researchers have used DEA to evaluate the performance of education organizations. Duh et al. (2014) found that for private universities the implementation of internal controls positively impacts teaching-related efficiency, and negatively impacts research-related efficiency. The authors did not find any significant impact for public universities. Kao

Fig. 2 Number of births. Source: Education statistics newsletter (2021). Retrieved from https://depart.moe.edu.tw/ED4500/Default.aspx

Number of births per year
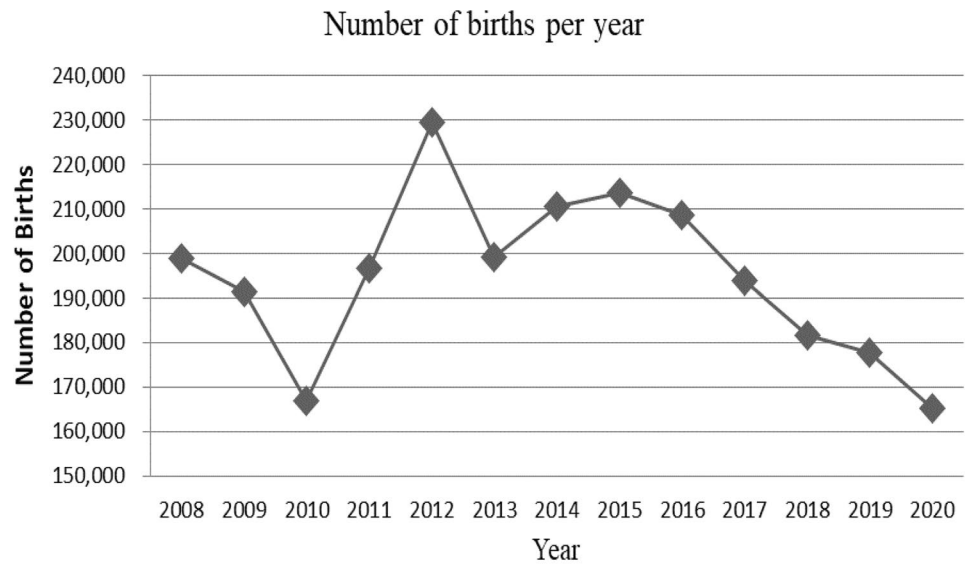
(1994) used a simplified DEA to evaluate the efficiency of industrial management departments at 11 5-year colleges in Taiwan, and compared the results to the Ministry of Education's evaluation. Kao found that departments with a better evaluation by the Ministry of Education evaluation were also better rated by the DEA.

Johnes and Johnes (1995) applied the CCR ratio model for evaluating research funding and performance of economics departments at 36 universities in England. They found that departments receiving research funding also showed better research quality.

Kao and Hung (2008) used DEA to evaluate the relative efficiency of 41 academic departments at Chengkung University, finding that academic departments with a higher/lower overall efficiency were more capable of using resources more/less effectively.

Avkiran (2001) used DEA for 36 universities in Australia to assess each school's overall performance, operating performance, and registration performance. The results demonstrate that for both overall performance and operating performance, the majority of schools evidenced technical efficiency and scale efficiency, but for registration performance, the majority of schools evidenced scale inefficiency. Avkiran suggested that to increase performance these schools should reduce their scale.

Abbott and Doucouliagos (2003) used the CCR and BCC models for assessing technical efficiency and scale efficiency at 23 Australian universities, finding that they demonstrated excellent technical efficiency and scale efficiency. The authors suggested that performance can be improved via full-time research personnel, full-time administrative personnel, capital expenditure, energy cost, and the number of undergraduates and graduate students.

Abramo et al. (2011) applied DEA to assess technical and distribution efficiency of research activities conducted by 78 Italian universities. They ranked universities based on their technical, allocative, and cost efficiency, finding that most universities enjoy high allocative efficiencies but low technical and cost efficiency on average.

Alabdulmenem (2017) examined the efficiencies of 25 public Saudi universities using the DEA framework, finding that most are efficient, while inefficiency is due to poor utilization of resources.

Tran and Villano (2018), using a multi-stage DEA network, found that higher education institutions in Vietnam have low efficiencies and are affected by age, location, ownership, and financial situation. Yang et al. (2018) used a two-stage DEA approach to measure the productivities of 64 research universities in China during the period of 2010–2013. They found that the universities improved productivity due to increased efficiency, and that on average, the universities experienced a technological deterioration.

Shamohammadi and Oh (2019) employed a two-stage DEA model to examine teaching and research performance in Korean private universities during the period 2010–2016, finding that that research output improves university performance, and that research-oriented universities are more efficient than teaching-oriented universities. Similarly, Ding et al. (2020) evaluated the performance of 38 non-homogenous departments in a Chinese university based on faculty and student research, to identify the most efficient. Tran et al. (2020) assessed resource allocation/misallocation of 61 Vietnamese universities using a two-stage DEA framework, finding they are more revenue efficient than teaching and research efficiencies. In addition, multidisciplinary Vietnamese universities outperform specialized ones.

MPI for education organizational inter-temporal performance evaluation

Since traditional DEA cannot be used to analyze inter-temporal efficiency, the MPI has been used in the literature.

Grosskopf and Moutray (2001) used the MPI to estimate the performance of high schools in Chicago between 1989 and 1994, after school-based management was implemented. They found that more than half of the schools had significantly improved productivity, yet a few failed to do so, especially those with higher average student expenditures. Flegg et al. (2004) used DEA and the MPI for assessing the operation efficiency of 45 universities in Britain between 1980 and 1993, finding that inefficient universities were purely due to technical inefficiency.

Femando and Cabanda (2007) applied the MPI and a multi-stage model for evaluating relative efficiency and productivity performance of 13 colleges of the University of Santo Thomas in the Philippines between 1998 and 2003. They found that a preponderant factor increasing productivity is efficiency change; and moreover, the overall technical efficiency was better than the innovative efficiency in each college. These findings suggest that using financial resources improves productivity performance. Worthington and Lee (2008) used DEA and MPI to analyze inter-temporal productivity change and the operation efficiency of 35 Australian universities between 1998 and 2003. The found an average 3.3% increase in annual productivity, with the productivity index of each school between − 1.8 and 13.0%, indicating that most schools, but not all, had improved productivity.

Visbal-Cadavid et al. (2017) analyzed the efficiencies of Colombian public universities using a DEA model, while using the Malmquist index to study the change in university productivity between 2011 and 2012. Wang et al. (2020) used an MPI approach to examine the efficiency, productivity, and change of technology in New Zealand universities, finding no improvement in productivity, which they attributed to a lack of funding. They recommended a change of personnel, student services, and equipment to improve productivity.

In conclusion, while DEA and MPI can indeed explore the operating performance of educational organizations, technology universities have been ignored in the literature. Thus, the purpose of our study. We used the MPI to investigate the operating performance of technology universities in Taiwan, and investigated the resource conversion performance of technology universities with higher/lower government subsidies to understand how government subsidizing policies affect technology universities' operating performance. In addition, our paper adds value to the literature through its methodological approach of combining

the MPI and the bootstrap method to calculate the confidential interval for eliminating confounding factors, and to test the MPI's significance (Hoff, 2006; Kneip & Simar, 1996; Simar, 1992; Simar & Wilson, 1999; Tortosa-Ausina et al., 2008). Our approach produces sufficient evidence demonstrating the rationality of MPI change of technology in Taiwan's universities.

Study design

Selection of variables

Given that the mission and characteristics of technology universities differ from general universities, our selected variables will also differ from those in the literature. In addition, we consider both the unique mission and educational characteristics of technology universities to select the variables (see Table 2).

Data collection

Data on the technology diffusion, school-industry collaboration cost, life-long learning, on-the-job continuing education cost, teaching and research hardware, software equipment incomes, basic technical learning tuition fees, technology diffusion, school-industry collaboration incomes, life-long learning, and on-the-job continuing education incomes were obtained from the account statement published by each technology university on their website. Data on school environment and the floor surface usage, number of professional instructors and employees, and the number of technology graduates were obtained from the Ministry of Education website, as was data on rewards and credits received from invention/patent competitions.

The input and output variables of national and private technology universities were tabulated, and those with incomplete information were eliminated. A total of 30 technological universities were included, with data between 2007 and 2011. Table 3 lists the definitions of variables, and Table 4 summarizes the descriptive statistics. Given that the universities use different levels of inputs and outputs, it is imperative to examine their relative efficiency in transforming inputs into outputs.

Table 5 presents the correlation coefficients of inputs and outputs. If the coefficients are positively correlated, this implies that more inputs generate more outputs, which comports with the DEA requirements. It is noted that all the correlation coefficients are positive. Therefore, these inputs and outputs hold isotonicity relationships and are thus justifiably included in the model (Golany & Roll,

Table 2 Input and output variables used in the literature

Variable	Code	Variable name	Authors
Input	I1	Technology diffusion and school-industry collaboration cost	Leitner et al. (2007); Abramo et al. (2011)
	I2	Life-long learning and on-job continue education cost	Abramo et al. (2011)
	I3	School environment and floor surface usage	Leitner et al. (2007); Shim (2003), Kounetas et al. (2011)
	I4	Number of professional instructors and employees	Salerno (2006); Leitner et al. (2007); Rad et al. (2010); Liu et al. (2004); Grosskopf and Moutray (2001); Shim (2003); Abramo et al. (2011)
	I5	Teaching and research hardware and software equipment	Liu et al. (2004)
Output	O1	Incomes from basic technology learning tuition fees	Abramo et al. (2011)
	O2	Technology diffusion and school-industry collaboration incomes	Leitner et al. (2007); Abramo et al. (2011)
	O3	Life-long learning and on-job continue education incomes	Abramo et al. (2011)
	O4	Number of technological graduates	Liu et al. (2004); Fandel (2007); Shim (2003), Abramo et al. (2011); Sohn and Kim (2012)
	O5	Rewards and credits received from winning invention/patent competitions	Leitner et al. (2007)

Table 3 Definition of input and output variables

Variable	Unit	Content
Input		
I1	NTD	Technology developed by research of a technology university to gain school-industry collaboration
I2	NTD	An expenditure of a technology university for opening on-the-job training based on their life-long learning philosophy
I3	m2	The total floor surface of the campus of a technology university
I4	Number of people	Number of professional instructors and administrative personnel
I5	NTD	Total number of software and hardware equipment that can be used for teaching or research
Output		
O1	NTD	Income from technology university students' tuition fees
O2	NTD	Technology obtained from research of a technology university for school-industry collaboration and making money
O3	NTD	Technology university incomes from opening on-the-job training based on their life-long learning philosophy
O4	Number of people	Number of technology graduates cultivated by a technology university
O5	Point	For international competitions: first place, 9 points, second place, 8 points; third place, 7 points, and excellence 6, points; For domestic competitions: first place, 5 points; second place, 4 points; third place, 3 points; and excellence, 2 points

1989). According to Golany and Roll (1989), sample homogeneity in DEA must meet the following criteria: All units perform the same tasks with similar objectives; all units perform under the same set of market conditions (this is of special importance in the analysis of non-profit organizations such as schools, army units, state hospitals, courts, etc.); and the factors (both inputs and outputs) characterizing the performance of all units in the group are identical, except for differences in intensity or magnitude.

Thus, we selected homogenous samples, and the selected variables can all be included into the DEA.

Research methodology

Technical efficiency measurement

Charnes et al. (1978) assessed the efficiency concept of Farrell (1957) and proposed a Charnes, Cooper, Rhodes (CCR) model for evaluating the relevant efficiency of multiple decision-making units. The CCR model assumes constant returns to scale. Assuming there are *n* decision-making units to be evaluated, and if each decision-making unit uses *m* items of input and *s* items of output, then given constant returns to scale, the technical efficiency (TE) of each decision-making unit is obtained using the following linear programming:

Table 4 Descriptive statistical analysis on input and output variables of Private and Public universities

Variables			Unit	Mean	Maximum	Minimum	SD
Public	Input	I1	NTD	236,540,413	732,541,726	21,974,607	170,083,941
		I2	NTD	13,393,818	47,788,280	744,197	9,297,358
		I3	m^2	186,030	297,973	66,223	60,973
		I4	Number of people	311	508	101	95
		I5	NTD	1,909,465,827	3,585,856,659	891,364,484	680,094,715
	Output	O1	NTD	434,037,373	604,339,943	100,501,958	135,475,808
		O2	NTD	245,352,159	762,922,169	22,847,875	177,053,100
		O3	NTD	14,485,021	52,976,310	933,975	9,887,708
		O4	Number of people	2259	3282	472	686
		O5	Point	108	441	0	118
Variables			Unit	Mean	Maximum	Minimum	SD
Private	Input	I1	NTD	53,085,984	216,356,045	14,640,391	34,365,952
		I2	NTD	20,046,140	753,354,445	193,974	75,170,043
		I3	m^2	113,108	208,761	62,735	35,067
		I4	Number of people	313	619	144	96
		I5	NTD	2,796,661,063	6,933,556,172	11,672,898	1,211,136,769
	Output	O1	NTD	820,294,880	1,627,048,190	302,064,118	263,130,614
		O2	NTD	57,123,458	248,278,740	15,005,933	39,880,126
		O3	NTD	21,586,676	678,702,955	0	68,269,939
		O4	Number of people	2467	4829	1099	795
		O5	Point	35	432	0	59

Table 5 Correlation analysis of input and output variables

Variables	Input				
	I1	I2	I3	I4	I5
Output					
O1	0.209	0.076	0.040	0.684	0.417
O2	0.998	0.046	0.809	0.444	0.038
O3	0.049	0.047	0.087	0.002	0.064
O4	0.214	0.100	0.350	0.872	0.346
O5	0.591	0.050	0.556	0.390	0.040

$Min\ \theta_o$

$s.t.$

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta_o x_{io}, \ i = 1, \ldots, m,$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro}, \ r = 1, \ldots, s,$$ (1)

$$\theta_o, \lambda_j \geq 0\ ; \forall\ i\ and\ r,$$

where n denotes the number of decision-making units; and x_{ij} and y_{rj} are the ith input quantity and the rth output quantity of the jth decision-making unit, respectively. This allows the technical efficiency θ_o to be calculated (TE $= \theta_o$). If TE $= 1$

(or 100%), then the decision-making unit is technically efficient. If TE < 1, then the unit has no technical efficiency. λ_j is used to determine if the jth decision-making unit can be the role model of the evaluated decision-making units: If $\lambda_j = 0$, then the jth decision-making unit cannot be, whereas a larger λ_j indicates yes.

By adding the constraint $\sum_{j=1}^{n} \lambda_j = 1$ to Eq. 1, constant returns becomes variable returns to scale. Here, the definition of efficiency obtained by the evaluated decision-making unit is pure technical efficiency θ_o (PTE $= \theta_o$). This is the BCC model (Banker et al., 1984) which measured the efficiency rate of technology universities in Taiwan.

Malmquist Productivity Index

The Malmquist Productivity Index (MPI) was first proposed by Caves et al. (1982). Its theoretical foundation is using the ratio of the distance function for defining a quantitative index, (Malmquist, 1953). The MPI is used to evaluate productivity changes of a decision-making unit at different periods. Although the MPI can be used to describe production technology with multiple inputs and outputs, it cannot investigate profit maximization or cost minimization goals of the evaluated units. Therefore, Färe et al. (1994) proposed a revised MPI model that decomposes

MPI (total productivity) into change in efficiency (Effch) and technical change (Techch), with MPI the product of Effch and Techch. We adopt an output-oriented model with one input and two outputs. Two periods (S and T) were used to express the MPI.

The term 'efficiency change' is the distance ratio of the efficiency frontier of an organization at a specific period. Take Organization A as an example; its efficiency change can be expressed as Eq. (2) below:

$$\text{Efficiency change (EC): } \frac{d^T(A_t)}{d^s(A_s)} = \frac{\overline{OA_t}/\overline{Ob}}{\overline{OA_s}/\overline{Oa}}, \tag{2}$$

where $d^T(A_t)$ denotes the distance of organization A_t at period T to the frontier of period T; and $d^s(A_s)$ denotes the distance of organization A_t at period S to the frontier of period S. If EC > 1, then the efficiency change has improved; if EC < 1, it has worsened; and if EC = 1, it has not changed.

TC is the distance ratio of the efficiency frontier of one period of the corresponding organization to another period. It is a cross-period comparison for understanding the efficiency frontier change between two periods. This is called the technical change (TC) of an organization from period S to period T. Organization A is used again to express this concept in Eq. (3):

Technological change (TC)

$$: \left[\frac{d^S(A_t)}{d^T(A_t)} \times \frac{d^S(A_S)}{d^T(A_S)} \right]^{\frac{1}{2}} = \left[\frac{\overline{OA_t}/\overline{Oa}}{\overline{OA_t}/\overline{Ob}} \times \frac{\overline{OA_S}/\overline{Oa}}{\overline{OA_s}/\overline{Ob}} \right]^{\frac{1}{2}} \tag{3}$$

If TC > 1, then TC has improved. If TC < 1, TC has worsened. If TC = 1, TC has maintained. By combining Eqs. (2) and (3), the MPI of each organization can be expressed as:

$$\text{MPI} = \text{EC} \times \text{TC} = \left[\frac{d^T(A_t)}{d^s(A_s)} \right] \times \left[\frac{d^S(A_t)}{d^T(A_t)} \times \frac{d^S(A_S)}{d^T(A_S)} \right]^{\frac{1}{2}}$$

$$= \left[\frac{\overline{OA_t}/\overline{Ob}}{\overline{OA_s}/\overline{Oa}} \right] \times \left[\frac{\overline{OA_t}/\overline{Oa}}{\overline{OA_t}/\overline{Ob}} \times \frac{\overline{OA_S}/\overline{Oa}}{\overline{OA_s}/\overline{Ob}} \right]^{\frac{1}{2}} \tag{4}$$

If MP > 1, then productivity has improved; if MP < 1, it has worsened; if MP = 1, productivity has maintained.

When the distance function of MPI is extended to multiple inputs and outputs, the following four linear programming equations can be used. Let's assume that there are n evaluated organizations and two periods (first period s and second period t). The equations are presented in (5), (6), (7) and (8):

$$\left\{ d_o^t(X^t, Y^t) \right\}^{-1} = \max \theta_o$$
$$st$$
$$-\theta y_{ro}^t + \sum_{j=1}^{n} \lambda_j^t y_{rj}^t \geq 0, \, r = 1, 2, ..., q \tag{5}$$
$$x_{io}^t - \sum_{j=1}^{n} \lambda_j^t x_{ij}^t \geq 0, \, i = 1, 2, ..., p$$
$$\theta, \lambda \geq 0 \, ; j = 1, 2, ..., n$$

The symbols used in the equations are defined below. (Note: the symbols are the same for Eqs. 6–8.)

- $X^t = (X_1^t, X_2^t, ..., X_p^t)$ is the sum of p input in period t, while $Y^t = (Y_1^t, Y_2^t, ..., Y_q^t)$ is the sum of q output in period t.
- $d_o^t(X^t, Y^t)$ is the distance to the efficiency frontier at period t of the oth evaluated organization at period t.
- θy_{ro}^t is the reference set of q output at period t of the oth evaluated organization.
- $\sum_{j=1}^{n} \lambda_j^t y_{rj}^t$ is the reference value λ_j^t of output at period t of the oth vs. the jth evaluated organization.
- x_{io}^t is the ith input value of the oth evaluated organization at period t.
- $\sum_{j=1}^{n} \lambda_j^t X_{ij}^t$ is the reference value λ_j^t of input at period t of the oth vs. the jth evaluated organization.

$$\left\{ d_o^s(X^s, Y^s) \right\}^{-1} = \max \theta_o$$
$$st$$
$$-\theta_o y_{ro}^s + \sum_{j=1}^{n} \lambda_j^s y_{rj}^s \geq 0, \, r = 1, 2, ..., q \tag{6}$$
$$x_{io}^s - \sum_{j=1}^{n} \lambda_j^s x_{ij}^s \geq 0, \, i = 1, 2, ..., p$$
$$\theta_o, \lambda_j \geq 0; j = 1, 2, ..., n$$

$$\left\{ d_o^t(X^s, Y^s) \right\}^{-1} = \max \theta_o$$
$$st$$
$$-\theta_o y_{ro}^s + \sum_{j=1}^{n} \lambda_j^t y_{rj}^t \geq 0, \, r = 1, 2, ..., q \tag{7}$$
$$x_{io}^s - \sum_{j=1}^{n} \lambda_j^t x_{ij}^t \geq 0, \, i = 1, 2, ..., p$$
$$\theta_o, \lambda_j \geq 0; j = 1, 2, ... n$$

$$\{d_o^s(X^t, Y^t)\}^{-1} = \max \theta_o$$

$$st$$

$$-\theta_o y_{ro}^t + \sum_{j=1}^{n} \lambda_j^s y_{rj}^s \geq 0, \; r = 1, 2, ..., q$$

$$x_{io}^t - \sum_{j=1}^{n} \lambda_j^s x_{ij}^s \geq 0, \; i = 1, 2, ..., p \tag{8}$$

$$\theta_o, \lambda_j \geq 0; \; j = 1, 2, ..., n$$

MPI and the bootstrap integrated method

The bootstrap method was developed by Efron (1979) based on nonparametric statistics. It uses data re-sampling to estimate statistical allocation to estimate the accuracy of statistical inference of an estimated sample. With the bootstrap method, a small sample is used for drawing the population allocation inference. This practical technique is implemented as follows:

Step 1 Randomly draw n samples, $X = (X_1, X_2, ..., X_n)$, from a population of an unknown probability distribution $F(X) \; X = (x_1, x_2, ..., x_n,)$ and establish an empirical probability distribution $\widehat{F}(X) \; \hat{F}(X)$, in which $\widehat{F}(X) \; \hat{F}(X)$ is the non-parametric maximum likelihood estimate (MLE) of the function of population allocation, $F(X)F(X)$.

Step 2 Assume the target population parameter of the study is $M = t(F)$ and the estimator is $\hat{M} = S(F)$. From the original random sample, $X_{1 \times n} = (x_1, x_2, ..., x_n)$, use the sampling and replacement method to extract B subsamples, $X_{n \times B}^* = (x_1, x_2, ..., x_B)$, of size n.

Step 3 The value of B depends on the given confidential interval. If less than 90%, at least 1000 sets of B are required for a normally distributed sample; and for a 95% confidential interval, at least 2000 sets are required (Efron & Tibshirani, 1993).

Step 4 Use this new sample ($N = B$) for calculating $\hat{M}^* = S(X^*)$ and to establish the probability distribution of $\hat{M}^*$, which is $\hat{F}^*(\hat{M}^*)$. Then, $\hat{F}^*(\hat{M}^*)$ is the bootstrap estimation of the random distribution of $\hat{M}$.

Step 5 Use the bootstrap distribution $\hat{F}^*(\hat{M}^*)$ to test hypotheses and related statistical inferences.

Since the MPI lacks a statistical inference foundation (Simar & Wilson, 1998), researchers have used the bootstrap method to analyze the level of sensitivity of the efficiency values generated by the MPI (Hoff, 2006; Kneip & Simar,

1996; Simar, 1992; Simar & Wilson, 1999; Tortosa-Ausina et al., 2008). Thus, to obtain the population allocation of MPI, we use the bootstrap method to carry out the statistical inference of MPI. Our approach comprised the following six steps:

Step 1 Assume n evaluated organizations and p input and q output items at periods t_1 and t_2. Make $X^t = (X_1^t, X_2^t, ..., X_p^t)$, $Y^t = (Y_1^t, Y_2^t, ..., Y_q^t) Y^t = \left(Y_1^t, Y_2^t, ..., Y_q^t \right)$, and $t = t_1, t_2$.

Step 2 Use t_1 and t_2 to estimate the efficiency of the evaluated organizations.

Step 3 For calculating the efficiency of periods t_1 and t_2 of each evaluated organization, the bootstrapping sampling generated B sets of the random sample.

Step 4 According to the efficiency of B sets of the random sample obtained from Step 3, output item Y was corrected and defined as $\hat{Y}_{jb}^t = (\hat{\theta}_j^t / \theta_{jb}^{*t}) Y_j^t, t = t_1, t_2$.

$$\widehat{Y}_{jb}^t = \left(\widehat{\theta}_j^t / \theta_{jb}^{*t} \right) Y_j^t, t = t_1, t_2$$

Step 5 The new efficiency $\hat{Y}_{jb}^t$ obtained for periods t_1 and t_2 according to the above steps, was used to calculate MPI (B sets) of each evaluated organization.

Step 6 Statistical inference was carried out by the standard bootstrap, percentile bootstrap, percentile-t, bias-corrected and accelerated bootstrap.

Empirical analysis

We used DEA to investigate the technical efficiency of technology universities in Taiwan. Secondly, the MPI was used to analyze productivity changes in technology universities in Taiwan. Lastly, the bootstrap method was used to carry out statistical inferences of the MPI.

Technical efficiency analysis

Table 6 indicates that between 2007 and 2011, there were 24 technology universities (80%) that had at least 1 year at the efficiency frontier (efficiency = 1): The National Taiwan University of Science and Technology for 5 consecutive years; with the National Kaohsiung University of Applied Sciences at 4 years. Secondly, the overall annual efficiency of technology universities was 0.839, indicating that the present input level was maintained. To reach the efficiency frontier, a school would need as little as a 16.1% increase in output. In other words, all schools demonstrated adequate school

Table 6 Annual technical efficiency of technology universities (2007–2011)

School	Acronym	2007	2008	2009	2010	2011	Mean
National Taiwan University of Science and Technology	NTUST	1.000	1.000	1.000	1.000	1.000	1.000
National Taipei University of Technology	NTUT	0.897	1.000	1.000	1.000	0.979	0.975
National Formosa University	NFU	1.000	0.863	0.795	1.000	1.000	0.932
National Kaohsiung First University of Science and Technology	NKFUST	0.719	0.852	0.972	1.000	0.970	0.903
National Kaohsiung University of Applied Sciences	NKUAS	1.000	1.000	0.838	1.000	1.000	0.968
National Kaohsiung Marine University	NKMU	0.868	1.000	0.871	1.000	0.937	0.935
National Yunlin University of Science & Technology	NYUST	1.000	1.000	0.897	0.945	1.000	0.968
National Pingtung University of Science and Technology	NPUST	1.000	0.874	0.986	1.000	1.000	0.972
National Penghu University of Science and Technology	NPUST	0.851	0.835	1.000	1.000	0.973	0.932
National Chin-Yi University of Technology	NCYUT	1.000	0.923	0.818	0.940	0.979	0.932
Southern Taiwan University of Science and Technology	STUST	0.953	0.704	1.000	0.869	0.661	0.837
Shu-Te University	STU	0.669	0.683	0.568	0.812	0.638	0.674
China University of Science and Technology	CUST	1.000	0.797	0.661	0.844	1.000	0.860
Overseas Chinese University	OCU	0.677	1.000	0.625	0.805	1.000	0.821
Ming Chi University of Technology	MCUT	0.718	0.719	1.000	0.771	0.979	0.837
St. John's University	SJU	0.730	1.000	0.811	0.783	0.969	0.859
China University of Technology	CUT	0.735	0.679	0.887	1.000	0.972	0.855
Tainan University of Technology	YUT	0.819	0.787	0.820	1.000	0.970	0.879
Jinwen University of Science and Technology	JUST	0.665	0.626	0.679	0.803	0.981	0.751
Chung Hwa University of Medical Technology	CHUMT	0.661	0.504	0.771	0.626	0.971	0.707
Tungnan University	TU	0.805	1.000	0.779	0.712	0.684	0.796
Takming University of Science and Technology	TUST	1.000	0.564	1.000	0.633	0.984	0.836
Fooyin University	FU	0.643	0.598	0.583	1.000	0.583	0.681
Hungkuang University	HU	0.558	0.671	0.638	0.797	1.000	0.733
Lunghwa University of Science and Technology	LUST	1.000	0.687	0.683	0.827	1.000	0.839
Minghsin University of Science and Technology	MUST	0.739	0.881	0.930	0.800	1.000	0.870
Vanung University	VU	0.789	1.000	0.679	0.577	0.966	0.802
Chienkuo Technology University	CTU	0.626	0.663	0.541	0.784	0.971	0.717
Nan Kai University of Technology	NKUT	0.769	0.584	0.797	0.665	0.819	0.727
Yu Da University	YDU	0.565	0.568	0.530	0.671	0.583	0.583
Mean		0.815	0.802	0.805	0.855	0.919	0.839
SD		0.151	0.166	0.156	0.137	0.137	0.106

operating performance, and no significant improvement was required. The school needing the greatest improvement required a 41.7% increase to reach the efficiency frontier, while the school needing the least required 2.5%. Thus, the majority of technology universities during the sample period have been improving their performances, specifically school-industry collaboration, opening life-long learning and on-the-job continuing education courses, and participating in invention/patent competitions.

We further classified technology universities into national and private. Table 7 and Fig. 3 indicates that the average efficiency of national technology universities was 0.952, significantly better than the 0.759 of private technology universities. Mainly that instructors of national technology universities can obtain a better retirement package—part of the government subsidy—and thus can attract better-quality

instructors and create a more professional image for industries. This in turn enables these schools to attain more frequent school-industrial collaboration. Furthermore, the school admission grades of students at national technology universities are better than those of students at private technology universities, making the former more preferred by companies.

Cheers, a Taiwanese magazine, annually conducts a survey on university graduates favored by decision-makers of 3000 major companies. The National Taiwan Technology University, and the National Taipei Technology University have been frequently ranked first and second. National technology university students' good competition results are another important reason. Thus, national technology universities' overall performance was better than the private universities.

Table 7 Annual technical efficiency of national and private technology universities (2007–2011)

Classification	2007	2008	2009	2010	2011	Mean	Mann–Whitney test (*P* value)
National school (N = 10)							0.032*
Mean	0.934	0.935	0.918	0.989	0.984	0.952	
SD	0.097	0.072	0.083	0.024	0.021	0.029	
Private school (N = 20)							
Mean	0.749	0.722	0.716	0.747	0.859	0.759	
SD	0.159	0.173	0.159	0.121	0.178	0.087	
Mean	0.815	0.802	0.805	0.855	0.919	0.839	
SD	0.151	0.166	0.156	0.137	0.137	0.106	

*Denotes a 5% significant level
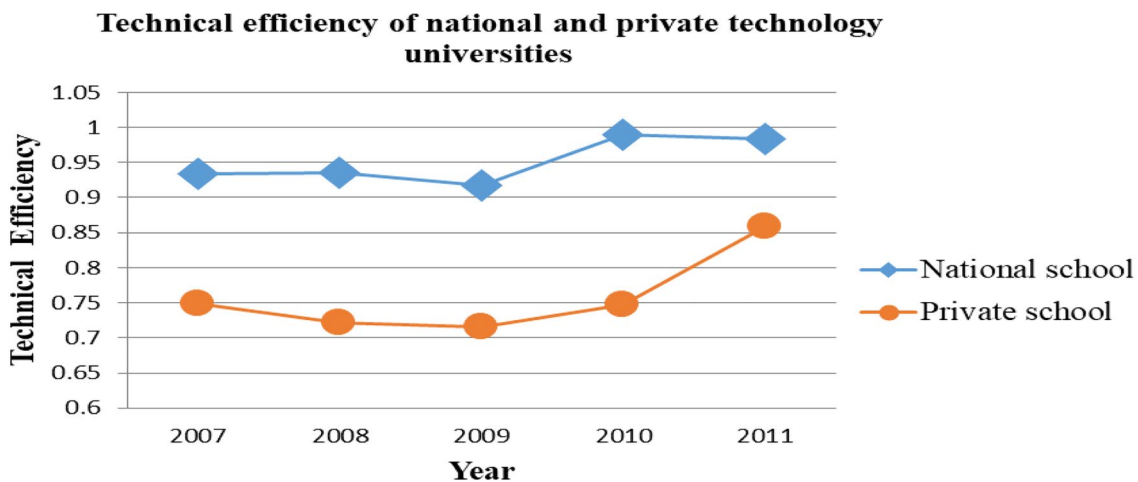
Fig. 3 Technical efficiency of national and private technology universities

Technology universities were classified based on the level of total income from government subsidies in order to understand the association between government subsidizing policies and technology universities' operating performance. In our sample, twelve technology universities had more than 40% of total income from government subsidies; the National Penghu University had the highest ratio, 62%, probably because the school's location is far from the island of Taiwan, making raising funds difficult. Eighteen technology universities had less than 20% of total income from government subsidies.

As shown in Table 8, the efficiency of schools with a higher proportion of governmental funding was 0.826, while the efficiency of universities with a lower proportion of governmental funding was 0.857. The two were not significantly different. Therefore, there is no guarantee that technology universities with a higher proportion of total income from governmental funding have a better operating performance. This is because *where* resources are acquired is not relevant; rather what matters is effectively using available resources to maximize effective use. Whether from government subsidies or self-raised funding, using resources efficiently and minimizing resource waste are critical for school operating performance.

Opportunities for school-industry collaboration and for employing technology university graduates may be affected by school location due to industrial clustering. Since Taiwan's industrialization after the Second World War, the country has experienced various stages of industrial and spatial reform before establishing a complex industrial development and spatial distribution system (Hsu, 2004; Kwok, 2005), with major industrial clusters in the northern, central, and southern regions of Taiwan's west coast. The majority of northern companies are electronic and information companies, especially computers and peripheral electronic components. Central companies are mostly traditional industries, including apparel, textile, shoes, and bicycles; as well as manufacturers of industrial machines, machine equipment, and precision machines. The southern region has iron and steel manufacturing, textiles, plastics, and transportation tool

Table 8 Annual technical efficiency of technology universities with high vs. low government subsidies

Classification	2007	2008	2009	2010	2011	Mean	Mann–Whitney test (P value)
A high percentage of government subsidies over the total incomes (N = 12)							0.026*
Mean	0.771	0.822	0.768	0.872	0.897	0.826	
SD	0.141	0.161	0.159	0.139	0.160	0.113	
A low percentage of government subsidies over the total incomes (N = 18)							
Mean	0.873	0.776	0.854	0.834	0.947	0.857	
SD	0.022	0.031	0.021	0.019	0.010	0.009	
Mean	0.815	0.802	0.805	0.855	0.919	0.839	
SD	0.151	0.166	0.156	0.137	0.137	0.106	

A high proportion of governmental subsidies means that government subsidies account for more than 40% of total income

A low proportion of governmental subsidies means that government subsidies account for less than 20% of total income

*Denotes a 5% significant level

Table 9 Annual technical efficiency of technology universities at northern, central, and southern regions of Taiwan (2007–2011)

Classification	2007	2008	2009	2010	2011	Mean	Kruskal–Wallis Test (P value)
Northern region (N = 14)							0.045*
Mean	0.807	0.788	0.815	0.789	0.933	0.826	
SD	0.147	0.189	0.156	0.140	0.129	0.103	
Central region (N = 7)							
Mean	0.804	0.815	0.730	0.848	0.967	0.833	
SD	0.194	0.173	0.129	0.118	0.066	0.110	
South region (N = 9)							
Mean	0.836	0.815	0.849	0.965	0.859	0.865	
SD	0.136	0.138	0.170	0.072	0.176	0.114	
Mean	0.815	0.802	0.805	0.855	0.919	0.839	
SD	0.151	0.166	0.156	0.137	0.137	0.106	

*Denotes a 5% significant level

manufacturers. Iron and steel manufacturers play an especially important role, along with heavy industry (Ching & Chou, 2007).

Therefore, we divided technology universities based on their location to investigate impacts of school location on school operating performance.

Table 9 indicates 14 schools in the northern region, with an average efficiency of 0.826; seven central schools, with an average efficiency of 0.833; and nine southern schools (including National Penhu University, which is not on the main island of Taiwan), with an average efficiency of 0.865. There was no significant difference among the three regions in their efficiency; mainly because each has national technology universities, thus eliminating regional educational differences. Furthermore, transportation has been much more convenient since high speed rail is available, which has significantly reduced the distance across Taiwan as well as urban–rural discrepancies. Therefore, school operating performance of technology universities in Taiwan is not significantly affected by location.

Productivity variance analysis

We used the MPI, EC, and TC as inter-temporal indices for measuring technology universities' operating performance. For the overall operating performance of these universities between 2007 and 2011, the average MPI was 1.035, indicating that the overall average productivity improvement was

Table 10 Average MPI of technology universities (2007–2011)

School	EC	TC	MPI
NTUST	1.182	1.131	1.336
NTUT	1.165	1.003	1.167
NFU	1.163	1.042	1.212
NKFUST	1.150	0.943	1.084
NKUAS	1.292	0.946	1.222
NKMU	1.090	1.114	1.213
NYUST	1.079	0.902	0.973
NPUST	0.975	0.956	0.932
NPUST	0.976	1.119	1.091
NCYUT	1.098	1.176	1.291
STUST	0.972	1.006	0.978
STU	0.954	0.796	0.759
CUST	1.040	1.024	1.065
OCU	1.026	0.996	1.022
MCUT	1.055	1.048	1.105
SJU	0.988	1.054	1.042
CUT	0.935	1.023	0.956
YUT	1.000	0.968	0.968
JUST	1.004	0.962	0.966
CHUMT	0.869	1.096	0.953
TU	0.996	0.944	0.940
TUST	1.000	0.946	0.946
FU	0.909	0.866	0.787
HU	0.973	1.009	0.982
LUST	0.886	0.989	0.876
MUST	0.982	1.204	1.182
VU	1.075	1.110	1.194
CTU	1.031	0.861	0.888
NKUT	0.964	1.061	1.023
YDU	0.968	0.925	0.895
Mean	1.027	1.007	1.035

3.5%. The efficiency change (EC) was 1.027, indicating that the EC improvement was 2.7%. The overall TC was 1.007; thus, the Technological Change (TC) improvement was 0.7% (See Table 10). Therefore, the EC and TC both affected productivity improvement; and more specifically, EC was more effective than TC in improving productivity. Nonetheless, the magnitude of improvement was not significant.

Based on our results we recommend enhanced budget management efficacy in order to plan space usage; establish a capital budget investment efficacy evaluation; formulate concrete plans for recruiting excellent instructors and for cooperative education programs.

For the overall operating performance between 2007 and 2011, 15 technology universities (50%) demonstrated improved productivity (MPI > 1), with their average MPI 1.150, indicating an average productivity improvement of 15%. No school had zero productivity improvement (MPI = 1), but 15 evidenced reduced productivity (MPI < 1), with an average MPI of 0.920. This indicated an average decrease in productivity of 8%.

Half of the technology universities between 2007 and 2011 evidenced worsened productivity in school operating performance. Thus, relevant departments should review the operating performance of technology universities and establish strategies for improvement, such as enhancing industry association, strengthening continuing education outcomes, encouraging students to participate in invention/competition competitions, improve the school's budget management capacity, integrate resource applications, and strengthen the budget allocation and auditing system. It is also important to use school funding effectively for purchasing books, instruments and equipment for teaching and research, and recruiting and cultivating excellent personnel (e.g., domestic as well as foreign teaching, research staff, and students) in order to improve school operating performance.

Half of the technology universities showed productivity improvement in school operating performance. This outcome should be maintained or further improved. Specifically, by establishing a comprehensive teaching quality auditing system; improving theses, patents; enhancing cooperation education efficiency; and increasing industrial production capacity in order to obtain income. Schools can also reward instructors for participating in research activities, and encourage students to carry out innovative inventions to improve their school's research, development, and innovation quality. It is also important to improve university instructors' international research awards in order to enhance international academic visibility so that school operating performance can be advanced.

MPI statistical inference

We used the confidential interval generated from the bootstrap method as the dummy variable for determining if the productivity indices were significant. When the confidential interval included 1, there was either no significant improvement or deteriorated productivity indices. When the confidential interval was greater than 1, there was a significant increase in the productivity indices, but if the confidential interval was less than 1, there was a significant deterioration of productivity indices. When assuming a 95% confidential interval, we re-sampled 3000 times using the bootstrap method, and then used the biased-corrected bootstrap (BC) to test productivity indices (Hoff, 2006; Löthgren & Tambour, 1999; Simar & Wilson, 1999; Tortosa-Ausina et al.,

Table 11 Comparison between original MPI and bootstrapping results

	Efficiency change (EC)			Technological change (TC)			Malmquist Productivity Index (MPI)		
	< 1	= 1	> 1	< 1	= 1	> 1	< 1	= 1	> 1
Original MPI	50	17	53	66	1	53	62	1	57
Bootstrapped MPI (Percentage of original MPI)	26 (52%)	8 (47.1%)	33 (62.3%)	36 (54.5%)	1 (100%)	32 (60.4%)	50 (80.6%)	1 (100%)	51 (89.5%)

2008). The bootstrapping results are not reported for space consideration.[1]

Our results show that the productivity change statement suggests that the average of 1.027% of overall EC between 2007 and 2011 indicated a 2.7% overall average improvement, and the average of 1.007% of TC during the same period indicating a 0.7% overall average. The results of the MPI change were all reliable.

Table 11 indicates index differences before and after bootstrapping. First, for EC, there were originally 50 ECs less than 1; 17 equal to 1; and 53 greater than 1. After bootstrapping, 26 ECs were significantly smaller than 1; 8 were significantly equal to 1; and 33 were significantly greater than 1. The level of change of these three classes was 48%, 52.9%, and 37.7%, respectively. For TC, there were originally 66 ECs less than 1; 1 equal to 1; and 53 greater than 1; but after using bootstrapping, 36 ECs were significantly smaller than 1; 1 was significantly equal to 1; and 32 were significantly greater than 1. The level of change of these three classes was: 45.5%, 0%, and 39.6%. For MPI, there were originally 62 ECs less than 1; 1 equal to 1; and 57 greater than 1, but after using bootstrapping, 50 ECs were significantly smaller than 1; 1 was significantly equal to 1; and 51 were significantly greater than 1. The level of change of these three classes was 19.4%, 0%, and 10.5%.

After using the bootstrap method for statistical analysis, technology universities demonstrated an average of 28.1% of significant change. This indicated that bootstrapping could eliminate part of the influence from sampling errors or other confounding factors.

Impact of environmental factors on performance

In addition to the performance evaluation, we also perform a truncated regression to examine the impact of environmental factors on university performance:

$$TE_j = a + \sum_{t=1}^{w} Z_{tj}\beta_t + \varepsilon_j, \quad j = 1, \ldots, n, \tag{9}$$

Here, $\varepsilon_j \sim N(0; \sigma_\varepsilon^2)$, $\varepsilon_j \geq 1 - a - \sum_{t=1}^{w} Z_{tj}\beta_t$, a is a constant term; ε_j is statistical interference; Z_{tj} is the tth value of the DMU_j specific observation variable. Given the importance of a school's intellectual capital we use it as the explanatory variable, and expect it to be related to the technical efficiency (TE_j) of the decision-making unit. Based on Lu (2012), the number of full-time teachers proxies for human capital; school-industry collaboration incomes proxies for relational capital; and hardware and software equipment for teaching and research proxies for structural capital. Table 12 indicates that human capital is the most crucial factor, followed by structural capital, and relational capital.

Conclusion

Science, innovation, and research and development are key drivers in Taiwan's economic growth. As such, the government of Taiwan has been investing in and funding technology universities. Despite the importance of these universities, little has been known about their performance and efficiency. Our study contributes to the literature by investigating the operating performance of technology universities in Taiwan, and analyzing their resource conversion performance with different levels of government subsidies to understand how government subsidizing practices affect technology universities' operating performance. Our results suggest that public universities are more efficient than the private universities. Moreover, we segregated our sample

Table 12 Results of the truncated regression analysis

	Coefficient	SE	Z-test	P value
Constant	153.363	0.656	233.688	0.000
Human capital	0.158	0.015	10.356	0.000*
Relational capital	0.022	0.013	1.675	0.047*
Structural capital	0.032	0.015	2.140	0.016*

*$P < 0.05$

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[1] The tables summarizing the results of the bootstrap tests are omitted for space reasons. However, we can share them upon request.

based on subsidy size as a percentage of the university funding; our results do not show any difference in the operating efficiency between universities with large or small government subsidies. This suggests that the source of funding is not relevant; what matters is whether the resources are effectively used to generate a high operating performance.

In addition, we analyzed the impact of efficiency change, technical change and MPI change on the operating performance. Our results, based on the MPI changes show that 50% of our sample universities improved their productivity by 15% during the sample period, while the other half experienced a drop in productivity of 8%. Analysis of the efficiency change and technical change suggests a positive improvement in university productivity; however, the change is not significant. Finally, we examined the impact of environmental factors on university performance, enabling us to identify additional determinants of university performance. Our results show that human capital is the most important factor in improving university performance, followed by structural capital (hardware and software equipment available for teaching), and relational capital i.e., the income generated by university-industry collaboration.

Management implications

Based on both performance evaluation and regression analysis, we offer the following suggestions for improving or maintaining the operating performance of technology universities.

Advancing human capital

Schools can establish flexible salaries to recruit excellent teachers from home and abroad, by offering a distinguished position, where the salary approximates that offered by foreign universities. This can significantly improve the teaching and research quality of schools. Secondly, it is important to enhance personnel exchange with other schools, both domestically and internationally, and to encourage staff taking advanced studies. Academic exchange should promote cross-school interaction. Schools can also select and subsidize excellent Taiwanese teachers and research personnel to study abroad or to collaborate with foreign researchers; then returning to Taiwan, they can improve their school's international competitiveness. Lastly, schools can establish a comprehensive teaching quality assessment and evaluation system to provide instructors professional assistance. By establishing an instructor teaching evaluation system and an instructor reward and elimination system, schools can effectively improve teaching quality.

Advancing structural capital

Campuses should be well planned according to their teaching, research, administration, activities, assembly, exhibition, sports, art and culture, education, service, parking, foodservice, shopping, recreational functions, living accommodations. In addition, schools could charge for the use of facilities, then classify the facilities depending on the level of profits generated, e.g., high, partial, and none.

Advancing relational capital

Technology universities can use their abundant teaching resources, excellent instructors, and professional teams to open pluralistic, multi-layer courses focused on both theory and practice. The universities can also assist companies for personnel training, and competitiveness enhancement. Depending on the purpose of corporate training and the number of trainees, the schools can establish programs for a specific company, or plan educational training according to a company's professional need.

Policy implications

Technology universities are expected to continue to play a key role in leading Taiwan's technological and industrial development. Therefore, these universities should be able to compete globally and be recognized for the quality of education and for their leading role in research. Government funding should thus focus on improving university research performance and creating world-class technology universities. The government can create research budgets for universities and research institutes that will participate in research projects of international teams, enabling universities to learn about research operations from foreign universities and elevate the breadth and depth of their own research. Secondly, the government should reward technology universities participating in domestic and international invention/patent competitions and winning awards, and invest in helping schools already possessing adequate invention/patent capacity to reach international excellence. We also recommend that universities that receive government funding should have a budget-managing system and show performance. Government education policies should be framed so that budget renewal will depend on previous performance evaluations of budget management.

We found that half of the universities in our sample have recorded a drop in efficiency. In addition, all universities are facing a decreased enrollment and a decreased birth rate, which universities must address. The Ministry of Education should incentivizing universities to identify

and restructure inefficient departments and optimize their resources.

Finally, inefficient universities should decide whether to focus on research or teaching. Teaching universities should allocate their resources to this area and develop students' job market skills and achieving higher operating efficiencies. Research universities should focus their efforts and resource allocations to innovations, technological development, and patents.

Limitations and suggestions

First, the selection of input and output variables is critical for using the DEA for performance evaluation. In our study, although the selection of input and output variables was based on the literature, as well as the mission and characteristics of technology universities, for future studies, depending on their focus, the input and output variables can be adjusted to comport with the specific objectives. Use of qualitative variables, such as graduate quality, could improve the performance evaluation.

Furthermore, our data covered a 5-year period. For future studies, a sample period can be constructed to observe long-term changes in productivity in order to enhance predictive power. Lastly, the quantitative model and methods used in this study can be applied to different industries for exploring different issues.

References

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

Abramo, G., Cicero, T., & D'Angelo, C. A. (2011). A field-standardized application of DEA to national-scale research assessment of universities. *Journal of Informetrics, 5*, 618–628.

Alabdulmenem, F. (2017). Measuring the efficiency of public universities: Using data envelopment analysis (DEA) to examine public universities in Saudi Arabia. *International Education Studies, 10*(1), 137–143.

Avkiran, N. K. (2001). Investigating technical and scale efficiencies of Australian universities through data envelopment analysis. *Socio-Economic Planning Sciences, 35*, 57–80.

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science, 30*, 1078–1092.

Caves, D. W., Christensen, L. R., & Diewert, W. E. (1982). Multilateral comparisons of output, input, and productivity using superlative index numbers. *Economic Journal, 92*, 73–86.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision-making units. *European Journal of Operational Research, 2*, 429–444.

Ching, C. O., & Chou, T. L. (2007). Differentiations in Taiwan's regional industrial clusters: The impacts of China effects. *Journal of Geographical Sciences, 49*, 55–79.

Clark, B. R. (1998). *Creating entrepreneurial university: Organizational pathways of transformation*. Pergamon Press.

Ding, T., Yang, J., Wu, H., Wen, Y., & Tan, C. (2020). Research performance evaluation of Chinese university: Anon-homogeneous network DEA approach. *Journal of Management Science and Engineering, 6*, 467.

Duh, R. R., Chen, K. T., Lin, R. C., & Kuo, L. C. (2014). Do internal controls improve operating efficiencies of universities. *Annals of Operations Research, 221*, 173–195.

Efron, B. (1979). Bootstrap methods: Another look at the jackknife. *The Annals of Statistics, 7*, 1–26.

Efron, B., & Tibshirani, R. J. (1993). *An introduction to the bootstrap*. Chapman & Hall.

Fandel, G. (2007). On the performance of universities in North Rhine-Westphalia, Germany: Government's redistribution of funds judged using DEA efficiency measures. *European Journal of Operational Research, 176*, 521–533.

Färe, R., Grosskopf, S., & Lovell, C. (1994). *Production frontiers*. Cambridge University Press.

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society Series A, 120*, 253–290.

Femando, B. I. S., & Cabanda, E. C. (2007). Measuring efficiency and productive performance of colleges at the university of Santo Tomas: A nonparametric approach. *International Transactions in Operational Research, 14*, 217–229.

Flegg, A. T., Allen, D. O., Field, K., & Thurlow, T. W. (2004). Measuring the efficiency of British universities: A multi-period data envelopment analysis. *Education Economics, 12*, 231–249.

Golany, B., & Roll, Y. (1989). An application procedure for data envelopment analysis. *Omega, International Journal of Management Science, 17*(3), 237–250.

Grosskopf, S., & Moutray, C. (2001). Evaluating performance in Chicago public high schools in the wake of decentralization. *Economics of Education Review, 20*, 1–14.

Hoff, A. (2006). Bootstrapping Malmquist indices for Danish seiners in the North Sea and Skagerrak. *Journal of Applied Statistics, 33*, 891–907.

Hsu, J. Y. (2004). The evolving institutional embeddedness of a late-industrial district in Taiwan. *Tijdschrift Voor Economische En Sociale Geografie, 95*, 218–232.

Johnes, J., & Johnes, G. (1995). Research funding and performance in U.K. university departments of economics: A frontier analysis. *Economics of Education Review, 14*, 310–314.

Kang, L. K., & Lee, W. C. (2009). An application of data envelopment analysis and Malmquist productivity index: A study of measuring the relative efficiency of technology universities in Taiwan. *Journal of Technological and Vocational Education, 3*, 73–105.

Kao, C. (1994). Evaluation of junior colleges of technology: The Taiwan case. *European Journal of Operational Research, 72*, 43–51.

Kao, C., & Hung, H. T. (2008). Efficiency analysis of university departments: An empirical study. *Omega, International Journal of Management Science, 36*, 653–664.

Kneip, A., & Simar, L. (1996). A general framework for frontier estimation with panel data. *Journal of Productivity Analysis, 7*, 187–212.

Kounetas, K., Anastasiou, A., Mitropoulos, P., & Mitropoulos, L. (2011). Departmental efficiency differences within a Greek university: An application of a DEA and Tobit analysis. *International Transactions in Operational Research, 18*, 545–559.

Kwok, R. Y. W. (2005). *Globalizing Taipei: The political economy of spatial development*. Routledge.

Leitner, K. H., Prikoszovits, J., Schaffhauser-Linzatti, M., Stowasser, R., & Wagner, K. (2007). The impact of size and specialisation on universities' department performance: A DEA analysis applied to Austrian universities. *Higher Education, 53*, 517–538.

Liu, L. C., Lee, C., & Tzeng, G. H. (2004). DEA approach for the current and the cross period efficiency for evaluating the vocational education. *International Journal of Information Technology & Decision Making, 3*, 353–374.

Löthgren, M., & Tambour, M. (1999). Bootstrapping the data envelopment analysis Malmquist productivity index. *Applied Economics, 31*, 417–425.

Lu, W. M. (2012). Intellectual capital and university performance in Taiwan. *Economic Modelling, 29*(4), 1081–1089.

Malmquist, S. (1953). Index numbers and indifference surfaces. *Trabajos De Estadistica y De Investigacion Operativa, 4*, 209–242.

Ministry of Education. (2011). *The founding of a hundred years of technical and vocational education special issue*. Ministry of Education.

Ministry of Education. (2019). *Technological and vocational education in Taiwan*. Ministry of Education.

Rad, S. H. M., Naderi, A. R., & Rad, S. M. M. (2010). Performance assessment of university departments using DEA: An exploratory study (Shahid Bahonar University of Kerman, Iran). *The IUP Journal of Managerial Economics, 8*, 63–76.

Reich, R. (1991). *The work of nations*. Knopf.

Salerno, C. (2006). Using data envelopment analysis to improve estimates of higher education institution's per-student education costs. *Education Economics, 14*, 281–295.

Schaafsma, H. (1996). Reflections of a visiting co-op practitioner. *Journal of Cooperative Education, 31*, 83–100.

Shamohammadi, M., & Oh, D. H. (2019). Measuring the efficiency changes of private universities of Korea: a two-stage network data envelopment analysis. *Technological Forecasting and Social Change, 148*, 119730.

Shim, W. (2003). Applying DEA technique to library evaluation in academic research libraries. *Library Trends, 51*, 312–332.

Simar, L. (1992). Estimating efficiencies from frontier models with panel data: A comparison of parametric, non-parametric and semi-parametric methods with bootstrapping. *Journal of Productivity Analysis, 3*, 167–203.

Simar, L., & Wilson, P. W. (1998). Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models. *Management Science, 44*, 49–61.

Simar, L., & Wilson, P. W. (1999). Estimating and bootstrapping Malmquist indices. *European Journal of Operational Research, 115*, 459–471.

Sohn, S. Y., & Kim, Y. (2012). DEA based multi-period evaluation system for research in academia. *Expert Systems with Applications, 39*, 8274–8278.

Taylor, S. (2001). Development of an integrated common support structure for the administration of cooperative education: Presented from a South Africa perspective. *Asia-Pacific Journal of Cooperative Education, 2*, 19–22.

Tian, Z. R., & Hsu, M. J. (2004). *The development of competitiveness indicators for public vocational high schools in Taiwan*. Ministry of Education, Central Office.

Tortosa-Ausina, E., Grifell-Tatje, E., Armero, C., & Conesa, D. (2008). Sensitivity analysis of efficiency and Malmquist productivity indices: An application to Spanish savings banks. *European Journal of Operational Research, 184*, 1062–1084.

Tran, C. D., & Villano, R. A. (2018). Measuring efficiency of Vietnamese public colleges: An application of the DEA-based dynamic network approach. *International Transactions in Operational Research, 25*(2), 683–703.

Tran, P. P., Kuo, K. C., Lu, W. M., & Kweh, Q. L. (2020). Benchmarking in Vietnam universities: Teaching and research and revenue efficiencies. *Asia Pacific Education Review, 21*, 197–209.

Visbal-Cadavid, D., Martinez-Gomez, M., & Guijarro, F. (2017). Assessing the efficiency of public universities through DEA. A case study. *Sustainability, 9*, 1416.

Wang, C.-N., Tibo, H., Nguyen, V. T., & Duong, D. H. (2020). Effects of the performance-based research fund and other factors on the efficiency of New Zealand Universities: A Malmquist productivity approach. *Sustainability, 12*, 5939.

Worthington, A. C., & Lee, B. L. (2008). Efficiency, technology and productivity change in Australian universities, 1998–2003. *Economics of Education Review, 27*, 285–298.

Yang, G. L., Fukuyama, H., & Song, Y. Y. (2018). Measuring the inefficiency of Chinese research universities based on a two-stage network DEA model. *Journal of Informatrics, 12*(1), 10–30.

Yung, C. S., & Hsu, M. J. (2006). *Industrial upgrading through innovation of technological and vocational education*. National Policy Foundation.