Heterogeneous Output Quality and Efficiency Evaluation of Polytechnic Higher Education Institutions via DEA*

Tsu-Tan Fu and Yung-Hsiang Lu**

Abstract

In this paper, we develop a quality adjusted DEA model to accommodate heterogeneous output quality in evaluating efficiency performance of polytechnic higher education institutions in Taiwan. The proposed model, adopting similar procedure of Fried et al(1999) in considering environmental effects, assumes input slacks from a quality unadjusted DEA may be partially attributed to the ignorance of differences in output quality. Since outputs of most polytechnic schools are different in quality, thus ignorance of such difference may result in bias in efficiency measurement and provide incorrect signal for resource allocation of schools in question. Conceptually, efficiency scores of those schools with better output quality will be undervalued if they are evaluated by a quality unconsidered DEA model. Empirical results of this paper have shown that public schools with better output quality are having about 11% improvement in efficiency scores measured by the proposed quality adjusted model than those measured by the quality unadjusted model. Results also indicate that after considering output quality difference, the mean efficiency of public schools becomes higher than that of private schools, which is the reverse results of using the quality unadjusted model. Accordingly, the efficiency ranking of public schools has also significantly improved by using the proposed quality adjusted model. Such reversal in efficiency score and ranking has been also evidenced in the efficiency analysis of S&T universities and TECH colleges.

Keywords:polytechnic higher education, technical efficiency, heterogeneous output quality, DEA, Taiwan

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1.Introduction

The polytechnic schools have played an important role in Taiwan industrial development for the last few decades by providing advance educated and skillful graduates for technological intensive industries. In 2003, Taiwan polytechnic higher education system consists of 17 Science and Technology(S&T) universities, 55 four-year technological colleges and 16 vocational junior colleges. There are 655,00 students enrolled in this academic system, which contains about 51.5% of total students in higher educations of Taiwan. However recent rapid expansion of number of schools and student enrollments in general university system, about 250% increase in the last two decades, has forced government to cut down its financial subsidy to each university including polytechnic schools and allow universities to be more administrative and financial independence. In addition, over 90% of Taiwanese university admission rate in recent years and favorable attitude of most prospective students toward the entrance of general university system also significantly reduced the number of student enrollment in vocational high schools and polytechnic colleges. Such plight in student enrollment reduction and financial insufficiency of polytechnic schools has been regarded to be even more pessimistic in the future since a significant decreasing trend of fertility rate in Taiwan is predicted. Such critical situation of polytechnic schools in Taiwan has exerted pressure on administrators and policy makers to raise concerns on the consolidation between schools and on whether individual school in polytechnic higher education system operating at the best possible level of cost efficiency.

Empirical analysis of the efficiency of higher education institutions has commonly employed the method of Data Envelopment Analysis(DEA). Major studies include those works measuring efficiency at school level, such as: Ahn, Charnes and Cooper (1988) on US universities in 1981-1985; Glass, Mckillop and O'rourke(1998) on UK universities in 1989-1992; Avkiran(2001), Abbott and Doucouliagos(2003) and Carrington, Coelli and Tao(2004) on universities in Australia. There are also a few studies measuring the efficiency at departmental level. For examples: Madden, Savage and Kemp(1987) assessed efficiencies of Economics departments in Australia universities. Jones and Johnes(1993) assessed efficiencies of Economics departments of UK in 1984-1988. Haksever and Muragishi(1998) and Colbert, Levary and Shaner(2000) studied the efficiency performance of MBA programs in the US. Tomkins and Green(1988) assessed cost efficiencies of UK accounting departments, whereas Beasley(1990) evaluated the efficiencies of chemistry and physics departments. It can be found that almost all previous researches focus on schools in general university system. There is virtually no research has attempted to analyze the efficiency of polytechnic universities or colleges.

One aspect regarding the heterogeneous quality of outputs among schools has often been ignored in previous efficiency studies. Since quality difference in outputs is apparent among most universities or polytechnic schools, therefore such ignorance could cause bias in efficiency measures and thus provide incorrect signal for resource allocation of schools in question. To insure the technical efficiency to be a valid performance measure in schools with various output quality, one must require all output variables used in DEA to be defined at the same given level of quality. A few of previous studies have attempted to consider such quality effect by treating quality of output variables as additional regular outputs or by breaking the original aggregated outputs into some detailed outputs in different quality in DEA. By a property of DEA, efficiency scores and possibility of being a full efficiency DMU tends to be higher as the number of inputs or outputs in the model increases. Therefore, adopting such ways of attempt in empirical analysis, one would often encounter the problem of losing discriminating power in ranking schools due to the size expansion of output vector for finite samples. The more the number of variables added as outputs, the worse the problem became. It is therefore an important research issue in finding appropriate means to accommodate output quality difference in schools and avoid such discriminating power losing problem in efficiency measurement using DEA.

The objective of this paper is to fill up such research gap. We attempt to propose a quality adjusted DEA model to adjust quantities of inputs based on the quality of outputs in schools in question. Such model also has appropriately solved the problem of losing power of discrimination in a DEA model setting. The proposed model will be used for the efficiency measurement of polytechnic higher education institutions in Taiwan. To my knowledge, this is the first paper that attempts to measure the efficiencies of polytechnic schools. This is also a frontier research in DEA on explicitly incorporating heterogeneous quality of outputs without scarifying the discriminating power in the efficiency measurement. The structure of this paper is as the followings. We will introduce the quality adjusted DEA model in section 2, this is followed by a data and variable section. Empirical results will be shown in section 4. The paper will end with some concluding remarks.

2.The Quality Adjusted DEA Model

DEA is a set of linear programming techniques that assist in identifying set of decision making units(DMUs) may be considered as best practice. Best practice units are regarded as DMUs with full efficiency and efficiency scores are assigned to other units by comparing them with best practice units(Abbott and Doucouliagos, 2003; Coelli, Rao and Battese, 2000). As compared to alternative popular methods for performance evaluation such as stochastic production frontiers, DEA is appealing to researcher since it can assess the technical efficiency of DMUs with multiple inputs and multiple outputs using only information on input and output quantities, apart from other benefits such as free of model functional form and residual distribution. Such unique data requirement characteristics, without requiring the information of prices, has made DEA to be widely employed in evaluating non-profit organizations or government regulated industries where prices of their outputs are generally not available in the market or not reflecting market value.

While higher education institutions can be characterized as non-profit organizations with multiple outputs and multiple inputs, the quality of outputs or educational services provided by these institutions are found to vary by institution. Ignoring such quality heterogeneity would result in imprecise or biased efficiency ratings. One way to accommodate such quality problem, which has been used in a few of previous studies, is to categorize an aggregate output into several detailed outputs by the levels of quality in output. For example, the number of papers produced by faculties has been commonly used as an indicator for evaluating the research performance of a university. However, a paper could have been published in a top-tier journal, fair international journal, local academic journal, or conference proceeding, reflecting quality difference in that paper. So could be the teaching service outputs of university, where the number of student enrollments can be broken into three outputs: the number of students in undergraduate, master and doctoral programs.

Therefore, by this way of considering heterogeneous output quality, we found that the output vector to be massive. As a result, problems of upward bias in efficiency scores and abnormal high number of full efficiency DMUs would be expected. Therefore, it is the challenge and interesting task for researchers to find a quality adjusted DEA model which could accommodate the quality heterogeneity of outputs and avoid the problem of over size in output vector.

In a paper by Fried et. al.(1999), they have developed a procedure of efficiency measure which is free of environment difference among DMUs. They have used a three-stage DEA procedure to consider such environment effects in the efficiency assessment, where impact of environment difference of DMUs on input slacks, resulted from the first stage DEA, has been adjusted in the second stage using regression method. The advantage of such way of adjustment using regressions is that possible impact of environmental variables on efficiency measurement can be all measured and fully adjusted to form a set of new adjusted input variables for computing efficiencies free of environment effect in the third stage DEA. Another important advantage of the procedure of Fried et. al.(1999) is that they have avoided the problem of over size in output vector. In fact, the number of inputs or outputs in the third stage will be the same as that of in the first stage.

By adopting similar idea of Fried et.al.(1999), we propose a three-stage quality adjusted DEA procedure to consider the heterogeneous output quality in efficiency measurement of Taiwanese polytechnic higher education institutions in this paper. This model would allow us to assess DMU performance at the same level of output quality and provide meaningful efficiency ranking of Taiwanese polytechnic schools. Since we assume that more resources will be consumed to produce those outputs with better quality, therefore the input oriented DEA is employed for empirical analysis.

In what follows, we introduce the proposed procedure in detail. In the first stage, we apply an input oriented DEA using the quality unadjusted outputs and inputs and compute efficiency scores for all schools. Given unadjusted output vector Y and input vector X, the Farrell's technical efficiency for the k-th DMU can be formulated as the following input oriented linear programming model developed by the Banker, Charnes and Cooper(1984), the BCC model,

$$
\begin{aligned}
&Min \quad E_k = \theta_k - \varepsilon\left[\sum_{i=1}^{m} S_{ik}^{-} + \sum_{r=1}^{n} S_{rk}^{+}\right] \\
&st \quad \sum_{j=1}^{N} \lambda_j X_{ij} - \theta_k X_{ik} + S_{ik}^{-} = 0 \\
&\qquad \sum_{j=1}^{N} \lambda_j Y_{rj} - S_{rk}^{+} = Y_{rk} \\
&\sum_{j=1}^{N} \lambda_j = 1 \quad , \lambda_j \geq 0 \quad , \forall j
\end{aligned} \tag{1}
$$

Where θ is efficiency score, E is non-Archimedean small number, λ_j is the optimal weight for the j the DMU, S^{-} and S^{+} are slack variables for input and output. By adopting (1), efficiency scores and slacks of radial and non-radial for each input variables can be computed for each DMU.

The second stage is to estimate the all input slacks equations using regression techniques. Dependent variables are those input slacks computed in the first stage. The independent variables are those output quality indicators to each input, which the input slacks regressions can be used to measure the effect of heterogeneous output quality on the inefficiency or the excess use of inputs used. Since input slacks can only be a positive value, the Tobit model is adopted for empirical analysis. Although Fried et. al.(2002) has suggested an alternative way, a stochastic frontier, to further separate the random component(noise) from the input slacks. But since such random effect is estimated insignificantly in this study, therefore we only present the results from the Tobit regressions.

The Tobit model for four input slacks in this paper can be formed as a regression model with input slack (ITS) assumed to be positive.

$$ITS_{ni} = f_n(Z_i, \beta_n, u_{ni}), \quad n = 1,\ldots,N, i = 1,\ldots,I \tag{2}$$

where ITS_{ni} is slack of the n-th input of the i-th DMU. u_{ni} is the random error. Zi is the vector of output quality variables of the I-th DMU.

Equation (2) will be used to predict the effect of output quality on input use. The expected input use based on the same output quality, the quality adjusted input, then will be computed by

$$x_{ni}^{A} = x_{ni} + [\max_i \{I\hat{T}S_{ni}\} - I\hat{T}S_{ni}] \tag{3}$$

where x_{ni}^{A} is the n-th adjusted input of the i-th DMU, $I\hat{T}S_{ni} = f_n(Z_i, \hat{\beta}_n)$ is the estimated the n-th input slack based on output quality embodied in the i-th DMU, the difference between $I\hat{T}S_{ni}$ and its max is used to adjust input at a same quality level. Equation (3) implies the higher the impact of output quality on inputs (slacks), the more the amount of input to be added (adjusted). After the adjustment in equation (3), the adjusted input x_{ni}^{A} can be regarded as the input free of the output quality effect.

In the third stage, we will use the quality adjusted input quantity (x_{ni}^{A}) and original output vector Y to recalculate efficiency score of each DMU by the BCC model of (1). The efficiency scores calculated in this stage are free of quality difference in outputs, which represents pure technical efficiency. It should be noted that the above mentioned three stage procedure is also used to evaluate a case which both impacts institutional characteristics and output quality are considered in the efficiency measurement of Taiwanese polytechnic schools in the later section of this paper.

3.Data And Variable

A three-year(2000–2002) panel data for 11 public and 38 private Taiwanese polytechnic higher education institutions, including 12 Science and Technology(S&T) universities and 37 four-year Technological(TECH) colleges, is used for empirical analysis. Data is collected from various publications of Ministry of Education of Taiwan.

3.1 Definition of Variables

Variables used in this study are defined in Table 1. The definition of those variables are described as followings:

Output variables

Output variables used are to represent three major functions of polytechnic higher education institutions such as teaching, research and social service. The number of full time student graduated annually(FTSG) is a variable commonly used as a proxy for university teaching service. However, to capture the unique characteristics of polytechnic schools on its emphasizing professional training at school, we add the number of professional certificates obtained by students in school(SPC) as another proxy variable for teaching service. As for the research performance, the number of faculty's research publications including journal articles and conference proceedings (FACRES) is a variable used as a proxy for outcome of research function. At last, the outcome of school's social service function is represented by a variable measuring the extension services provision, number of students registered in credit and non-credit hour continue education programs(EXTS).

Output quality variables

Five output quality variables are employed to represent quality difference in outputs of teaching, research and social service provided among schools. To measure possible difference in teaching quality, the student faculty ratio(STU/FAC), defined as number of full time student divided by number of full time faculty, is used as a quality indicator for teaching. The teaching quality in a small class is assumed to be higher than that in a big class. Therefore, the larger the STU/FAC is , the lower the quality of teaching could be. Another quality indicator for teaching output is the ratio of university students to total student enrollments(UG/CG), defined as number of students registered in 4-year program divided by total number of students including those registered in 2-year program. The UG/CG is a polytechnic school specific variable reflecting its special student system which mixing with university and junior college programs in a school. The teaching quality requirement for a 4-yearprogram is generally assumed to be higher that that quality for 2-year junior college program. Therefore, we expect those schools with lower STU/FAC or higher UG/CG values to consume more resources given the same amount of teaching output FTSG.

The quality indicator for another teaching output, student's professional certificate obtained(SPC), is the ratio of better certificates obtained(AB/SPC), defined as the number of grade A or grade B professional certificates obtained divided by to the total number of professional certificates obtained. Since professional certificate at A and B grade require higher skill and knowledge, thus those schools with the larger value of AB/SPC would have higher quality in output SPC and would consume more resources at a given level of SPC.

As for the research performance, the ratio of number of papers published in journals to total papers published in journals per full-time faculty(NJFAC) is used as a quality indicator for the research output FACRES. A paper published in a journal is general regarded to have higher quality and to consume more resources than a paper published in a conference. Therefore, a school with high NJFAC is doing better in quality of research production and supposed to use more inputs at given level of FACRES.

The last quality indicator used in this paper is to address the quality of output for university social service(EXTS). Such indicator is defined as the ratio of number of students registered in extension programs with credit hour to the total number of students registered in extension programs with and without credit hour, CREDIT/EXTS. An extension class with credit usually requires higher standard to attend than a non-credit class. Thus, a school with higher CREDIT/EXTS would expect to provide better quality in social service and consume more inputs than that with lower value of CREDIT/EXTS.

<u>**Input Variables**</u>

Four variables are considered to be inputs for education production of Taiwanese polytechnic schools in this paper. The number of full time equivalent faculty(FTEFAC) and the number of administrative and supporting staff(STAFF) are variables for labor inputs. The concurrent expense(CONEXP) and capital expense(CAPEXP), defined in Table 1, are other commonly used variables as capital inputs in the university production process.

<u>**Institutional Characteristics**</u>

Two variables are used to reflect characteristics of polytechnic higher education institutions in Taiwan. The school ownership(OWNER) is a dummy variable for distinguishing public and private school. OWNER =1 for public owned polytechnic school and =0 for private owned school. The school type (STYPE) is another dummy variable to indicate school difference in its academic programs: STYPE =1 for my for S&T university and STYPE = 0 for technological (TECH) college.

3.2 Sample Statistics

Table 2 shows descriptive statistics including means and variances of output, input and output quality variables used in our sample schools by institutional characteristic variables. By comparing the inputs and outputs between public and private schools, some interesting results deserved to be mentioned. For those two teaching outputs, table 2 indicates that both average student body(FTSG) and average professional certificates produced(SPC) in public schools is smaller than that in private schools. On the contrary, averagely public schools have provided higher amount of services on research(FACRES) and extension(EXTS) than private schools. In term of input usage, table 2 shows that public schools still consume more on supporting staff(STAFF) and concurrence expense(CONEXP) than private school, even though the school size of public schools is found to be smaller than that of private schools.

Comparing the outputs and inputs between S&T universities and TECH colleges in table 2, we find mean values of all output variables in S&T universities are greater than those in TECH colleges. Therefore, the average outputs of teaching, research and social services produced by S&T universities outperform those produced by TECH colleges in Taiwan. However, table 2 also indicates that averagely the S&T universities have used more labor inputs and expenses than the TECH colleges. Thus, the ranking of productivity and efficiency between these two types of schools is not clear and will be investigated in the later section.

As for the output quality, those mean statistics of public and private schools in table 2 indicate that except for social service(CREDIT/EXTS), public schools have relative high values in variables for teaching quality(STU/FAC, UG/CG and AB/SPC) and much better research quality(NJFAC) than private schools. Difference in output quality has also been evidenced between S&M universities and TECH colleges, table 2. All output quality indicators in table 2 show the dominance of S&M universities in all output quality over TECH colleges. Table 2 also indicates that among those quality indicators for teaching, research and social service, the UG/CG of teaching quality and NJFAC of research quality are found to have the widest difference between schools with different ownerships or types.

4.Empirical analysis

The proposed three-stage quality adjusted DEA model is employed for empirically assessing the efficiencies of polytechnic schools in Taiwan. The proposed quality adjusted DEA model is assumed to be an input oriented and with variable return to scale(VRS), which is a BCC type of DEA model. To fully capture possible effects of output quality and to exam additional effect from other factors such as institutional characteristics on the efficiency measurement, two models are considered for analysis. Model 1 assumes input slacks will be only influenced by those output quality factors, whereas Model 2 adds institutional characteristics as additional possible factors affecting input slacks. By comparing the results between these two models, one can test the power of impact from quality and institutional effects. There are 49 Taiwanese polytechnic schools to be analyzed. However, to increase the sample size, data of these 49 schools for three years (2000-2002) is empirically used in proposed DEA model. Nevertheless, the final efficiency results of these schools will be presented by the average values of these three years in the tables of this paper.

4.1 The First Stage Results

In the first stage, only those quantity data of variables for four outputs and four inputs as listed in Table 1 are used in the BCC model. Since this BCC model does not include output quality variables, we named it as the "quality unadjusted DEA model". The results of the quality unadjusted DEA model (or of the stage 1) are shown in the first row of Table 3. The mean efficiency score of the total sample is 0.858, which means an average score of 86% of efficiency level as compared to the best practice schools. It also implies a 14% room of possible inefficiency improvement for polytechnic schools in Taiwan. Results of the stage 1 are also found to vary by different types of schools. While the mean efficiency score of public school (0.807) is lower than that of private school (0.873), the mean efficiency score of S&T universities (0.842) is also lower than that of TECH colleges (0.863).

In addition, if we rank the schools by their efficiency scores, a school with the highest score will be ranked as the first place (rank =1) and the second highest score will be ranked as the second place (rank =2) , and so on. Results of average rank of efficiency in Table 3 for the stage 1 show that the average ranking of public schools (rank = 29) is higher than that of private schools (rank = 24), so is the S&T universities to TECH colleges. Such results of efficiency ratings and rankings between various types of schools are somewhat unexpected intuitively. However, these results may be biased since no output quality variables has been considered and well adjusted in the quality unadjusted DEA model in the first stage.

4.2 The Second Stage Results

In the second stage of the proposed procedure, both radial and non-radial input slacks calculated from the first stage quality unadjusted DEA model are summed up first and will be used as the dependent variables in the second stage Tobit regressions for input slacks.

There are two regression models representing two different scenarios to be estimated in this stage. In model 1, we assume that those input slacks can only be affected by five output quality variables including STU/FAC, UG/CG, AB/SPC, NJFAC and CREDIT/EXTS, whereas we assume input slacks can also be affected by some institutional characteristics variables such as OWNER and STYPE in model 2.

Table 4 shows results of Tobit regressions for all four input slacks. Except the CREDIT/EXTS, all other variables have shown to be significant in explaining at least one input slack regressions. Results of Model 1 in Table 4 indicating significant negative impacts of STU/FAC and NJFAC as well as significant positive impact of UG/CG on input slacks are found consistently across all regressions in Model 1. Other variables such as AB/SPC and CREDIT/EXTS are found to be insignificant in all regressions of Model 1. Such findings indicates that input slacks or the inefficient input usages of polytechnic schools in Taiwan can be significantly explained by heterogeneous quality in outputs of teaching and research among schools. The quality difference in output for extension service however plays no role in affecting input slacks. Since output quality can strongly affect the input usages, therefore the efficiency scores will be biased if one fails to consider output quality difference in the efficiency measurement using quality unadjusted DEA, as in the first stage.

Tobit regression results of Model 2 are also presented in Table 4. In addition to those five output quality variables, two institutional factors, OWNER and STYPE, are included in the regressions. The results of output quality variables in Model 2 are similar to those findings in Model 1, except the AB/SPC is also found to be significant in CONEXP input slack equation. Besides, institutional factors are found to have negative significant impact on those STAFF and CONEXP input slack equations. However, the total effects of such additional institutional variables seem to be weak since the likelihood function values are almost the same for both models. Therefore, one may conclude that the heterogeneous output quality has dominant effect on the inefficiency use of inputs for polytechnic schools of Taiwan.

The estimated parameters from Tobit regressions of Table 4 are used for adjusting all input quantities of every DMU to be free of output quality difference, using the equation (3) in section 2. These adjusted inputs will then be used for assessing the efficiency score by the proposed quality adjusted DEA model in the third stage.

4.3 The Third Stage Results

In this stage, those quality adjusted inputs from the second stage and original outputs as in the first stage are the data to be used for measuring efficiencies of all DMUs. The BCC model of DEA as in the first stage is again employed. We will also compare results from the third stage with results from the first stage and to exam the significance in efficiency difference via the Mann-Whitney test.

The results of the third stage DEA can be seen in Table 3. The mean efficiency score of the whole sample of the third stage for Model 1, adjusted only by the quality of outputs, is 0.872, which is 1.6% higher than that of the first stage quality unadjusted DEA. The mean efficiency score of the whole sample in Model 2 of the third stage, adjusted by output quality and institutional characteristics, is 0.843, a 1.7% lower than that in the first stage DEA. For ease of comparison, we use [A] to represent stage 1 model, [B] to represent Model 1 of stage 3, and [C] to represent Model 2 of stage 3. The differences in mean efficiencies of the whole sample between stages and models, [A] vs [B] and [A] vs [C] in table 3, are tested to be insignificant, which implies effects of output quality and institutional factors on efficiencies of DMUs to be insignificant for the whole sample. However, some very interesting results can be found in the following sub-sample comparisons.

In comparing effect of output quality consideration on mean efficiencies of public schools between stage 1 and stage 3, we find that mean efficiency score increases from 0.807 of stage 1 to 0.895 of stage 3 for Model 1, about 10.9% increase. On the contrary, we find mean efficiency score of private schools decrease from 0.873 of stage 1 to 0.866 of stage 3 for Model 1, about 0.8% decrease. Such findings on efficiency changes show a substantial impact of output quality consideration on efficiencies of DMUs. As a result, the mean efficiency of public schools becomes higher than that of private schools after considering the output quality. Table 3 also indicates that the average rank of public schools moves ahead from 29th place to 21st place, whereas such rank of private schools drops from 24th place to 26th place. Thus, public schools become much higher in efficiency score and better in ranking after considering the output quality factors, whereas private schools become worse in both efficiency score and ranking after the quality adjustment. Such results seem reasonable because public schools have better output quality than private schools, thus efficiencies of the former (latter) would increase (decrease) if the proposed quality adjusted model is used.

Similar findings can be found for different types of schools. Those S&T universities with better output quality than TECH colleges are found to have lower mean efficiency score (0.842) than that of TECH colleges (0.863) in stage 1 without quality adjustment. However, after inputs adjusted by output quality, efficiency score of public schools (0.911) becomes higher than that of TECH colleges (0.860), Model 1 of stage 3 ([B]) in Table 3. The magnitude of change in efficiency due to quality consideration is measured to be 8.2% for S&T universities and –0.3% for TECH colleges. In addition, results of the effect of quality adjustment on the rank of schools are shown in Table 3. After the quality adjustment, the average rank of S&T universities has improved from the 27^{th} place to the 18^{th} place, whereas the average rank of TECH colleges has dropped from 24^{th} place to 27^{th} place.

Finally, table 3 also shows results from Model 2 of stage 3 ([C]), an alternative model with considering both output quality and institutional factor. If we compare results between Model 1 and Model 2, we may find the difference in efficiency scores of these two models to be very small. By comparing the average rank of S&T universities between [B] and [C] in Table 3, we also find the average ranking of such schools to be very close. This is also the case for the TECH colleges. Therefore, it is plausible to conclude that the heterogeneous output quality possesses dominant effect on efficiency measurement of polytechnic schools in Taiwan. The possible effect of those institutional factors of polytechnic schools tends to be insignificant.

5.Concluding Remarks

In this paper, we develop a quality adjusted input oriented DEA model to accommodate the heterogeneous output quality in the efficiency evaluation of polytechnic higher education institutions in Taiwan. The proposed model, adopting similar procedure of Fried et al(1999) in considering environmental effects, assumes input slacks from a quality unadjusted DEA may be partially attributed to the ignorance of differences in output quality among schools. Since outputs for most polytechnic schools are difference in quality, thus ignorance of such difference may result in bias in efficiency measurement. Those schools with better output quality usually consume more inputs than those schools with lower output quality, given the same amount of output. Therefore, conceptually the efficiency scores of those schools with better quality in outputs would be under valued by a quality unadjusted DEA model. Similarly, efficiency scores of those schools with lower output quality would be over valued. Previous studies have attempted to consider such quality effect by treating quality of output variables as additional regular outputs or by breaking the original aggregated outputs into some detailed outputs in different quality in DEA. However, by adopting such ways of attempt in empirical analysis, one would often encounter the problem of low discriminating power in ranking schools for finite samples. Therefore, in this paper we intend to develop our model to be a model that can consider the heterogeneous quality in outputs and also avoid the problem of losing discriminating power in ranking efficiency.

Empirical findings from this study have confirmed our conceptual expectations. Results of efficiency measurement from the quality adjusted DEA model are quite different from those from the quality unadjusted model. In our data, the output quality of public schools is averagely higher than that of private schools, so is the output quality of S&T universities to that of TECH colleges. Our empirical results have shown that mean efficiency of public schools is found to be lower than that of private schools by the quality unadjusted DEA model. Accordingly, the efficiency ranking of public school is worse than that of private schools. However, after considering output quality difference in the quality adjusted DEA model, the mean efficiency score of public schools become higher than that of private schools. The efficiency ranking of public schools has also significantly improved by the proposed quality adjusted model. Such reversal in efficiency score and ranking has been also evidenced in the efficiency analysis of S&T universities and TECH colleges. Lastly, the additional effect of institutional characteristics on efficiencies of polytechnic schools is found to be insignificant.

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Table1：Definition of Variables

Variable	Definition
<u>Output</u>	
FTSG	Number of full-time students graduated annually
SPC	Number of professional certificates obtained in school by students
FACRES	Number of faculty's research publications including in journals and conference proceedings
EXTS	Social or extension services by number of students registered in classes with credit and non-credit hour in continual education program
<u>Input</u>	
FTEFAC	Number of full-time equivalent faculties
STAFF	Number of supporting staffs
CONEXP	Concurrent expenses excluding wages and fringe benefits of faculties and staffs (in million NT$)
CAPEXP	Capital expenses excluding land and building expenses (in million NT$)
<u>Output Quality</u>	
STU/FAC	Number of full-time students per full-time faculty
UG/CG	Number of students enrolled in 4-year university program/total number of students enrolled
AB/SPL	Number of grade A and grand B professional certificates obtained/SPC
NJFAC	Number of journal publications per full-time faculty
CREDIT/EXTS	Number of students registered in extension classes with credit/EXTS
<u>Institutional Factor</u>	
OWNER	Dummy variable for school ownership, OWNER=1 for public school, OWNER= 0 for private school
STYPE	Dummy variable for school type, STYPE = 1 for Science and Technology (S&T) university, STYPE = 0 for technological college (TECHC)

Table 2： Descriptive statistics of variables for Taiwanese polytechnic schools by school ownership (OWNER) and School type (STYPE), 2000-2002

Variable	Mean	OWNER		STYPE	
		Public [11][a]	Private [38]	S&T [12]	TECH [37]
Output					
FTSG	2,355 (893)	1,636 (740)	2,563 (830)	2,692 (1,098)	2,246 (804)
SPC	1,766 (1,550)	802 (640)	2,058 (1,625)	2,326 (1,633)	1,598 (1,501)
FACRES	223 (218)	442 (358)	160 (92)	459 (319)	147 (87)
EXTS	865 (714)	948 (598)	841 (750)	1,248 (635)	741 (701)
Input					
FTEFAC	308 (99)	266 (118)	321 (91)	376 (101)	286 (89)
STAFF	98 (49)	147 (67)	84 (30)	149 (64)	82 (28)
CONEXP	201 (98)	247 (174)	187 (60)	324 (114)	161 (47)
CAPEXP	102 (48)	88 (61)	106 (44)	131 (50)	92 (44)
Output Quality					
STU/FAC	27.0 (4.9)	21.1 (3.1)	28.7 (4.0)	26.2 (6.6)	27.3 (4.3)
UG/CG	0.374 (0.286)	0.600 (0.380)	0.309 (0.219)	0.790 (0.244)	0.239 (0.123)
AB/SPC	0.138 (0.149)	0.179 (0.139)	0.126 (0.151)	0.159 (0.133)	0.131 (0.155)
NJFAC	0.387 (0.322)	0.792 (0.460)	0.270 (0.120)	0.646 (0.483)	0.303 (0.192)
CREDIT/EXTS	0.302 (0.288)	0.299 (0.292)	0.303 (0.290)	0.438 (0.238)	0.258 (0.291)

Notes：a: figure inside [ ] is the number of sample school b: standard deviation in parenthesis

Table 3： Comparisons of results of efficiencies and ranks in stage 1 and stage 3

Scenario		Mean Efficiency	OWNER		STYPE	
			Public [11][a]	Private [38]	S&T [12]	TECH [37]
Quality unadjusted DEA：						
Stage 1	**[A]**	0.858 (0.121)	0.807 (0.165)	0.873 (0.103)	0.842 (0.131)	0.863 (0.119)
Quality adjusted DEA：						
Stage 3 Model_1	**[B]**	0.872 (0.093)	0.895 (0.103)	0.866 (0.090)	0.911 (0.086)	0.860 (0.092)
Stage 3 Model_2	**[C]**	0.869 (0.087)	0.904 (0.099)	0.859 (0.082)	0.918 (0.072)	0.853 (0.087)
[A] v.s [B]	U test[d]	-0.21	-2.03**	-0.89	-1.94*	-0.86
	([B]-[A])/[A]	1.6%	10.9%	-0.8%	8.2%	-0.3%
[A] v.s [C]	U test	-0.11	-2.26**	-1.43	-2.00**	-1.28
	([C]-[A])/[A]	1.3%	12.0%	-1.6%	9.0%	-1.2%
Average rank	**[A]**	-	29	24	27	24
	[B]	-	21	26	18	27
	[C]	-	18	27	17	28

Notes：a: figure inside [ ] is the number of sample school

b: standard deviation in parenthesis.

c: The * , ** and *** indicate that the parameter estimate is significantly different from zero at the 10 percent, 5 percent

d: U test is the Mann-Whitney test

Table 4：Tobit regression results for input slacks

Independent Variable	Model_1				Model_2			
	Dependent Variable				Dependent Variable			
	FTEFAC	STAFF	CONEXP	CAPEXP	FTEFAC	STAFF	CONEXP	CAPEXP
Constant	200.017***	98.938***	154.110***	85.011***	191.241**	162.993***	270.728***	107.255**
Output Quality								
STU/FAC	-5..387***	-3.384***	-5.598***	-2.548***	-5.303***	-2.169***	-5.192***	-2.749***
UG/CG	64.259***	58.574***	122.234***	27.238*	68.751*	39.538**	50.312**	15.853
AB/SPC	-10.818	4.119	39.636	16.304	-11.359	5.676	44.816*	17.385
NJFAC	-89.248***	-33.331***	-66.325***	-42.533***	-89.808***	-50.347***	-76.910***	-41.155***
CREDIT/EXTS	-4.472	-5.639	4.693	7.853	-3.902	-0.201	5.320	6.431
Institutional Factor								
OWNER					-1.811	-34.256***	-16.211	4.390
STYPE					4.531	-13.110	-42.862*	-11.427
σ	69.980***	37.513***	65.992***	40.229***	69.974***	35.437***	64.666***	40.079***
Log likelihood function	-610.123	-543.244	-600.513	-555.611	-610.107	-538.031	-598.717	-550.311

Notes：The * , ** and *** indicate that the parameter estimate is significantly different from zero at the 10 percent, 5 percent and 1 percent level, respectively.