Estimating the Efficiency of Philippine Public High Schools Using Spatio-Temporal Stochastic Frontier Analysis

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This paper proposes a method for modeling production function of education using a stochastic frontier model with spatial temporal terms. Using a unique dataset that combines school achievement scores with school characteristics from 2005-2008, the efficiency of 4,900 public high schools in the Philippines in converting school inputs into test scores was estimated. Results show that the average inefficiency is at 41% and that there is a significant positive spatial externality in efficiency, which means that efficiency in one school can spill over to its neighbors. The model was found to be robust to various environmental variables included in the estimation. The results of the study will be important to guide policy makers in allocating limited resources to public schools.

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In the Philippines, the continued debate on increasing the number of years for basic education has brought education into the forefront of policy-making and implementation. The interest on increasing the number of years, as input, has made people question the role of such in improving student performance, as output. This issue has clearly made people realize the importance of the returns on education and educational policies supported or brought about by the government and the educational sector. Thus, this article relates student achievement to a variety of subjects.

The performance of students in the Philippines has been mediocre as compared to other countries in Asia and the Pacific as evidenced by the results of the 2007 Trends in International Mathematics and Science Study, which ranked the country 41st out of 46 countries that participated. Thus, the perception that the educational system is ineffective is widely believed because of the presence of such dismal test scores. Therefore, this paper looks at the inefficiency of the educational systems by looking into how a variety of academic inputs relate to actual test achievement scores of Filipino students.

Since this paper relates student outcomes (test scores) to school inputs, the education production function (EDF) provides the framework on how student achievement is a result of various school inputs, student-specific characteristics (individual and household), and community characteristics as what Todd and Wolpin (2003) argued. It is also important to note that educational institutions in this model are treated as producers of achievement (Greenwald, Hedges, & Laine, 1996) where the commonly employed means of inputs used in schools that are related to student achievement (Hanushek, 1996) are: (1) the real resources of the classroom (teacher education, teaching experience, and teacher-pupil ratios); (2) financial aggregates of resources (expenditure per student and teacher salary); and, (3) measures of other resources in schools (specific teacher characteristics, administrative inputs, and facilities). However, there can be problems of quantifying the aspects from specification to measurement and data availability.

This paper continues the study of Orbeta (2008) that estimated the role of school characteristics on school achievement test scores using school level data from the National Achievement Test administered to second year high school students during school years 2005-2006, 2006-2007, and 2007-2008, which were obtained from the National Education Testing Center. The exam measured students' competencies in English, Science, Math, Filipino, and Social Studies. This study looks at how education productivity can maximize educational outcomes where educational productivity can be defined by the level of technical efficiency, which attempts to maximize student learning and organizational policy outcomes while a set of financial and human resource inputs are being utilized (Stiefel, Schwartz, Rubenstein, & Zabel, 2005).

The results of this study can provide schools incentive structures that encourage better performance and recognize differences of students, teachers, and schools. The concept of efficiency as applied to education would be useful in analyzing and, possibly, allocating education budgets (inputs) in relation to student outcomes.

METHODOLOGY

Public high school data gathered in this study included student test scores (outputs) taken over various periods of time and school indicators (inputs) such as student-teacher ratio, student-classroom ratio, and student-seat ratio. Most models assess the efficiency of outputs and inputs but separately takes into account the spatial and temporal variables. This study applied spatio-temporal stochastic frontier to simultaneously assess all factors since various periods of time and the location of a school can affect test scores of public high school students.

In stochastic frontier modeling, several models were proposed given a panel data. Assuming constant factor coefficients over time, Battese and Coelli (1995) postulated a time-decaying inefficiency (improving learning curve) as

$$y_{it} = f(x_{it};\beta) \exp(v_{it}) \exp(-u_{it}) \tag{1}$$

where

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

The production function $f(x_{it};\beta)$ may take Cobb-Douglas general form or a more general exponential or a non-linear function. y_{it} refers to the output of producer at time $t.x_{it}$ is a vector of factors of production. v_{it} is the pure error, which we allow to be autocorrelated. $\exp(-u_{it})$ measures technical efficiency, which is assumed to follow a strictly non-negative stochastic distribution, usually assumed to be half-normal or exponential in the literature. γ and β are parameters to be estimated from data. The back fitting algorithm introduced by Hastie and Tibshirani (1990) for additive models was modified to simultaneously estimate a group of parameters vis-à-visiterative processes and is said to be superior compared to certain panel data models (Barrios & Lavado, 2010).

Over time, the producers get to realize their failure to adopt efficient technologies and correct it soon after wherein more efficient production process is applied. Battese and Coelli (1995) further postulated that inefficiencies are functions of some exogenous variables and used the maximum likelihood technique in parameter estimation.

Many stochastic frontier models for panel data failed to account for temporal dependencies (improving learning curve of producers) and spatial externalities (adoption of efficiency-enhancing technologies among the producers in a spatial neighborhood) simultaneously. Ignoring this aspect of the information contained in the panel data will result to inadequate differentiation of the producer's efficiency-inducing potentials, hence, may result to inferior estimates of technical efficiency coefficients.

A spatial-temporal stochastic frontier model is postulated by Landagan and Barrios (2007) and Barrios and Lavado (2010):

$$y_{it} = f(x_{it};\beta)\exp(v_{it}(v_{it-1};\rho))\exp(-u_{it}(w_{it}, z_{it};\lambda,\phi)) \quad (3)$$

where

$$v_{it} = \rho v_{it-1} + \psi_{it} \quad (4)$$

$$u_{it} = \frac{1}{1+\exp\left(-\left(\lambda\sum_{j=1}^{N} w_{ij}u_{jt} + \phi z_{it}\right)\right)} + \varepsilon_{it} \quad (5)$$

$$w_{ij} = \begin{cases} 1, & \textit{if i and j are spatially related} \\ 0, & \textit{(from the same province) otherwise} \end{cases} \quad (6)$$

Taking the logarithm of the equation in (3) results to

$$ln y_{it} = ln f(x_{it};\beta) + v_{it}(v_{it-1};\rho) - u_{it}(w_{it}, z_{it};\lambda,\phi) \quad (7)$$

Following Reifschneider and Stevenson (1991), we model technical efficiency as a function of environmental factors z_{it}. In addition, however, we allow for spatial autoregression (SAR), as proposed by Pace and Barry (1997), among neighboring units through $\sum_{j=1}^{N} w_{ij}u_{jt}$, where w_{ij} are elements of a spatial weight matrix W, which describes pair-wise spatial distance between observations. Also, we allow for autocorrelation in the error term v_{it}. ψ_{it} and ε_{it} are white noise processes and various corresponding parameters are to be estimated.

A dynamic production parameter in the equation may account for the spatial externalities accounted by the spatial indicator, but will require more complicated estimation procedure. Temporal dependence in the residual v_{it} can also be generalized to higher-order AR process, but the time-adjustment process of inefficiency reduction might be contaminated for much longer autoregressions given a short panel.

The additivity of the models presented in equations (3) to (6) will make estimation via the hybrid backfitting algorithm feasible. The backfitting algorithm used is similar to Landagan and Barrios (2007), and is given as follows:

1. Equations (4) and (7) are combined to estimate β and ρ simultaneously using generalized least squares. Technical efficiency u_{it} will be reflected in the residuals as

$$\widehat{u_{it}} = ln y_{it} - f(x_{it};\hat{\beta}) - \hat{\rho}e_{it-1} \quad (8)$$

where e_{it-1} is the lagged residuals of the fitted model. $\widehat{u_{it}}$ contains information on λ and ϕ.

2. Given $\widehat{u_{it}}$, equation (5) is fitted using a general linear model to estimate λ and ϕ.
3. The estimate of technical efficiency is given by

$$TE = exp\left(-\frac{1}{1+\exp\left(-\left(\hat{\lambda}\sum_{j=1}^{N} w_{ij}\widehat{u_{jt}} + \hat{\phi}z_{it}\right)\right)}\right) \quad (9)$$

The simultaneous estimation of β and ρ yield optimality over individual estimation in pure backfitting of an additive model. Following, the argument of Landagan and Barrios (2007), this will not necessitate further iteration of the algorithm.

The inclusion of autoregression in the error of the production function will account for the producers' learning curve while also accounting for the possible cumulative effect of production errors. The spatial externalities that can vary over time and across spatial neighbors help characterize efficiency/inefficiency differences among the producers.

DATA AND RESULTS

The data was taken from National Achievement Test (NAT) administered to second year students of high school during school years 2005-2006, 2006-2007, and 2007-2008. The exam measured competencies in English, Science, Math, Filipino, and Social Studies.

School characteristics were obtained from the Basic Education Indicator System (BEIS) School Statistics Module. The BEIS was started in 2002

Table 1
Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Production Input					
ln(student-teacher ratio)	8532	3.49	0.36	1.10	6.71
ln(student-classroom ratio)	8532	3.89	0.22	0.85	5.54
ln(student-chair ratio)	8532	0.22	0.49	-1.73	4.19
Environmental Variables					
Dropout rate	8532	0.06	0.04	0.00	0.54
Dropout rate – sq.	8532	0.01	0.01	0.00	0.30
Student-toilet ratio	8532	132.16	135.06	5.50	2002.00
Proportion locally-funded teachers	8532	0.11	0.18	0.00	1.00
Science high school – indicator	8532	0.01	0.10	0.00	1.00
Integrated school – indicator	8532	0.09	0.29	0.00	1.00
More than one shift – indicator	8532	0.07	0.26	0.00	1.00
HE room – indicator	8532	0.34	0.47	0.00	1.00
IA workshop – indicator	8532	0.19	0.39	0.00	1.00
Computer room - indicator	8532	0.62	0.49	0.00	1.00
Library – indicator	8532	0.64	0.48	0.00	1.00
Clinic – indicator	8532	0.24	0.43	0.00	1.00
Cafeteria – indicator	8532	0.42	0.49	0.00	1.00
Principal-in-school – indicator	8532	0.62	0.48	0.00	1.00
SEF (Province/City)-funded teacher – indicator	8532	0.24	0.43	0.00	1.00
SEF (Municipality)-funded teacher – indicator	8532	0.13	0.34	0.00	1.00
LGU-funded teacher – indicator	8532	0.12	0.32	0.00	1.00
PTCA-funded teacher – indicator	8532	0.08	0.28	0.00	1.00

Table 2
Comparative Production Estimates of Two Alternative Models

	Math	Science	English	Filipino	History	Total
Half-normal TE						
ln(student-teacher ratio)	0.037 ***(0.015)	0.010 (0.014)	-0.009 (0.010)	0.003 (0.010)	-0.003 (0.010)	0.006 (0.011)
ln(student-classroom ratio)	-0.199 ***(0.025)	-0.130 ***(0.022)	-0.109 ***(0.016)	-0.078 ***(0.016)	-0.097 ***(0.016)	-0.115 ***(0.017)
ln(student-chair ratio)	-0.007 (0.009)	-0.020 ***(0.008)	-0.020 ***(0.005)	-0.018 ***(0.006)	-0.027 ***(0.006)	-0.019 ***(0.006)
constant	5.036 **(0.090)	4.872 ***(0.082)	4.903 ***(0.062)	4.791 ***(0.098)	4.794 ***(0.061)	4.860 ***(0.068)
Spatio-Temporal TE						
ln(student-teacher ratio)	0.035 (0.021)	-0.001 (0.019)	-0.011 (0.014)	-0.007 (0.014)	-0.001 (0.015)	0.002 (0.015)
ln(student-classroom ratio)	-0.079 ***(0.033)	-0.010 (0.031)	-0.038 *(0.022)	-0.004 (0.023)	-0.006 (0.023)	-0.028 (0.023)
ln(student-chair ratio)	-0.007 (0.010)	-0.027 ***(0.009)	-0.018 ***(0.007)	-0.016 **(0.007)	-0.033 ***(0.007)	-0.021 ***(0.007)
constant	3.956 ***(0.134)	3.867 ***(0.123)	4.168 ***(0.088)	3.939 ***(0.091)	4.037 ***(0.094)	4.011 ***(0.092)
Figures in parentheses are standard errors						

by the Research and Statistics Division of the Department of Education (DepEd) for monitoring and performance evaluation. Among the variables that were used in this study are: enrollment, number of shifts, classroom utilization, school furniture, position of teaching personnel, and local government unit (LGU) funded teachers.

BEIS and NAT datasets for the three school years were merged using unique school IDs assigned by DepEd for each school. A total of 4,151 schools were merged for SY 2005-2006, 4,143 schools for SY 2006-2007, and 4814 schools for SY 2007-2008.

Table 1 presents the list of variables used in the study as well as the corresponding summary statistics. The production units include the 8,352 public secondary schools; the output is school-level National Achievement Test (NAT) average scores of students. Three factors of production were included: (a) student-teacher ratio, (b) student-classroom ratio, and (c) student-seat ratio. A Cobb-Douglas production function is specified for both models.

For the production input, data on student-teacher ratio, student-classroom ratio, and student-chair ratio were included. As seen in the data, there is a lack of teachers, classrooms, and chairs in Philippines schools. For the environmental variables, dropout rates and student-toilet ratios were included. Dropout rates can go as high as 0.54 in certain schools and there is a severe lack of toilets that will serve the student population. All the other variables are indicators of presence or absence of certain facilities in the school such computer room, library, clinic, and cafeteria. There are also indicators of whether the school is classified as "science" (where the curriculum is enriched with math and science courses not normally taken in other schools) or "integrated" (where students take elementary and high school "continuously" without the need to graduate from elementary to go into high school). The presence

Table 3
Spatio-Temporal Technical Efficiency Model Estimates - Schools Division-based Neighborhood (Model 1)

Environmental Variables	NAT Subjects					
	Math	Science	English	Filipino	History	Total
Dropout rate	13.37 ***(2.57)	17.32 ***(3.49)	19.12 ***(3.04)	14.50 ***(3.01)	17.92 ***(3.87)	17.45 ***(3.23)
Dropout rate – sq.	-37.08 ***(12.57)	-56.22 ***(17.79)	-56.20 ***(14.10)	-41.24 ***(14.06)	-59.57 ***(20.39)	-53.66 ***(15.85)
Student-toilet ratio	0.0008 ***(0.0002)	0.0009 (0.0002)	0.0009 ***(0.0002)	0.0004 (0.0004)	0.0009 ***(0.0002)	0.0008 ***(0.0002)
Proportion locally-funded teachers	0.38 (0.25)	-0.18 (0.43)	-0.35 (0.38)	0.13 (0.31)	-1.00 *(0.55)	-0.31 (0.40)
Science high school	-15.12 (692.10)	-14.79 (748.51)	-14.72 (759.44)	-13.79 (616.29)	-14.11 (589.60)	-14.12 (539.93)
Integrated school	0.29 *(0.16)	0.34 **(0.16)	0.41 **(0.18)	0.74 ***(0.18)	0.60 ***(0.13)	0.49 ***(0.15)
More than one shift	1.00 ***(0.11)	0.35 **(0.14)	0.02 (0.20)	-1.13 (0.73)	0.04 (0.15)	0.20 (0.16)
HE room	0.07 (0.09)	0.17 (0.12)	0.11 (0.11)	0.01 (0.12)	0.24 **(0.11)	0.13 (0.11)
IA workshop	-0.08 (0.11)	0.17 (0.14)	-0.21 (0.16)	-0.15 (0.17)	0.15 (0.13)	0.06 (0.14)
Computer room	0.33 ***(0.09)	0.16 (0.12)	-0.03 (0.10)	0.08 (0.10)	0.21 *(0.11)	0.15 (0.11)
Library	0.10 (0.09)	0.18 (0.12)	0.01 (0.11)	-0.07 (0.11)	0.09 (0.12)	0.06 (0.11)
Clinic	0.34 ***(0.11)	0.44 ***(0.13)	0.49 ***(0.12)	0.28 ** (0.14)	0.53 ***(0.12)	0.46 ***(0.12)
Cafeteria	-0.05 (0.09)	0.10 (0.11)	0.03 (0.10)	-0.21 *(0.12)	0.22 **(0.10)	0.07 (0.10)
Principal-in-school	-0.18 **(0.08)	0.25 **(0.11)	0.00 (0.10)	-0.15 (0.10)	0.00 (0.10)	0.06 (0.10)
SEF (Province/City)-funded teacher	0.14 (0.09)	0.17 (0.13)	-0.11 (0.12)	-0.08 (0.12)	0.06 (0.13)	0.03 (0.12)
SEF (Municipality)-funded teacher	0.10 (0.12)	0.01 (0.15)	0.05 (0.14)	0.03 (0.13)	0.11 (0.15)	0.03 (0.14)
LGU-funded teacher	0.26 **(0.12)	0.06 (0.15)	-0.12 (0.14)	0.11 (0.12)	-0.01 (0.15)	-0.03 (0.14)
PTCA-funded teacher	0.19 (0.14)	-0.04 (0.19)	0.09 (0.15)	0.09 (0.15)	0.06 (0.18)	0.01 (0.17)
Constant	-4.32 ***(0.15)	-4.72 *** (0.20)	-4.69 ***(0.18)	-4.32 ***(0.17)	-4.96 ***(0.20)	-4.68 ***(0.18)
λ	0.11 ***(0.00)	0.14 *** (0.00)	0.17 ***(0.01)	0.17 ***(0.01)	0.19 ***(0.01)	0.16 ***(0.01)

of a variety of teachers with different sources of funding is also indicated in this list.

In Table 2, the production function parameter estimates for both models are similar, indicating that they both estimate similar empirical structures characterizing education production. Parameter estimates $\hat{\beta}$ corresponding to production inputs may be interpreted as elasticities. A respective one percent change in student-classroom ratio (more students per classroom) and in student-chair (more students per chair), holding all others constant, is related with a significant negative percentage change in NAT scores.

Table 3 (Model 1) presents the spatio-temporal efficient model estimates of schools and division-based neighborhood while Table 4 (Model 2) presents the technical efficiency estimates. The sparse spatial autoregression SFM estimated through the modified backfitting algorithm (Model 1) and the ordinary SFM estimated using maximum likelihood estimation in a truncated normal error distribution (Model 2) are compared in an education production function setting. For Model 1 efficiency equation, 18 determinants (fourcontinuous and 14 dummy indicators) were used to characterize household's income-generating efficiency/inefficiency. Spatial neighborhood among schools was defined as follows:

$$w_{ij} = \begin{cases} 1, & \textit{if schools i and j are from the same} \\ 0, & \textit{province otherwise} \end{cases}$$

Model 2 requires careful specification of the iterative estimation process since it involves matrices with large dimension in the likelihood function. Model 1, on the other hand, is easier to handle in the empirical implementation since the factors of production and the factors of efficiency are dealt separately at different steps in the iterative process.

Model 1 yields an average estimate of technical efficiency of 0.9537 (s.d.=0.0568) or about 5% inefficiency in education production. Model 2 on the other hand, produced an average estimate of technical efficiency of 0.6051 (s.d.=0.1142) or 41% inefficiency. The higher average technical efficiency estimate from Model 1 can be attributed to the significant amount of the residual that is further accounted into the effect of spatial externalities, added to the inefficiency in the case of Model 2. The technical efficiency estimates from Models 1 and 2 yield a correlation of 0.4009, indicating that the models were able to identify the same households as inefficient/efficient. The correlation between technical efficiency estimates with the output (log NAT score) is 0.3410 for Model 1, while 0.1418 for Model 2.

Table 4

Technical Efficiency Estimates (Model 2)

Specification	Math	Science	English	Filipino	History	Total
Time-invariant Half-normal	0.559 (0.149) [0.23, 0.91]	0.577 (0.129) [0.24, 0.91]	0.637 (0.100) [0.29, 0.93]	0.558 (0.091) [0.28, 0.88]	0.680 (0.101) [0.30, 0.94]	0.605 (0.114) [0.26, 0.93]
Spatio-Temporal						
Region	0.928 (0.090) [0.49, 1.00]	0.941 (0.074) [0.52, 1.00]	0.958 (0.051) [0.67, 1.00]	0.956 (0.052) [0.70, 1.00]	0.960 (0.047) [0.65, 1.00]	0.950 (0.060) [0.59, 1.00]
Schools Division	0.927 (0.088) [0.51, 1.00]	0.937 (0.076) [0.54, 1.00]	0.954 (0.055) [0.65, 1.00]	0.958 (0.048) [0.67, 1.00]	0.957 (0.051) [0.62, 1.00]	0.948 (0.061) [0.60, 1.00]
Student Population Decile	0.964 (0.060) [0.49, 1.00]	0.970 (0.049) [0.54, 1.00]	0.978 (0.029) [0.71, 1.00]	0.978 (0.028) [0.74, 1.00]	0.977 (0.032) [0.67, 1.00]	0.973 (0.038) [0.62, 1.00]
Figures in parentheses are standard errors; Figures in brackets are ranges						

In Model 1, estimates of the coefficient λ indicate that there is significant positive spatial externality in efficiency, that is, efficiency in one school spills over to its neighbors. It is interesting that efficiency is a quadratic function of drop-out rate. Probably having more drop-out students eases the problem of crowded schools and insufficient infrastructure up to a certain extent, thus the positive marginal effect. However, the marginal effect of an increase in drop-out rate on technical efficiency decreases after a certain level. There are also interesting differences in the efficiency of NAT subject scores where Math is the lowest and History the highest in both models. Since NAT scores are considered outputs in both models, there is a need by education researchers and policymakers to assess the combination of inputs such as those found in the models.

CONCLUSIONS

This study applied stochastic frontier analysis with spatial and temporal components to determine the efficiency of educational inputs on students' achievement scores. It also looked at how changes in inputs such as the number of classrooms, chairs, and teachers can affect test scores. As seen in Table 2, having a high student-classroom and student-chair ratio can negatively impact the scores of high school students. As for the spatio-temporal aspects of the model, there is a significant positive spatial externality in efficiency, which means that efficiency in one school spills over to its neighbors. This is a good sign that areas with good schools can "influence" or have an impact on each other's improvement. As Hanushek (1996) stated, resources alone may not be sufficient to guarantee high achievement scores but adequate resources are surely necessary. Thus a combination of resources and environmental factors are necessary to improve the overall test achievement scores of students.

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