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Rouselle F. Lavado and Erniel B. Barrios

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For comments, suggestions or further inquiries please contact:
The Research Information Staff, Philippine Institute for Development Studies
5th Floor, NEDA sa Makati Building, 106 Amorsolo Street, Legaspi Village, Makati City, Philippines
Tel Nos: (63-2) 8942584 and 8935705; Fax No: (63-2) 8939589; E-mail: publications@pids.gov.ph
Or visit our website at http://www.pids.gov.ph

Spatial-Temporal Dimensions of Efficiency among Electric Cooperatives in the Philippines

By Rouselle F. Lavado[a*], Erniel B. Barrios[b]

[a]*Philippine Institute for Development Studies, Rm. 311 NEDA sa Makati Building, 106 Amorsolo St., Legaspi Village, Makati City, Philippines; rlavado@mail.pids.gov.ph, rlavado@gmail.com*
[b]*School of Statistics, University of the Philippines, Magsaysay Ave., Diliman, Quezon City, Philippines; erniel.barrios@up.edu.ph , ernielb@yahoo.com*

Abstract

The efficiency of 119 electric cooperatives in the Philippines from 1990-2002 is analyzed using a stochastic frontier model augmented with spatial-temporal terms, addressing the underestimation of technical efficiency usually encountered among maximum-likelihood based methods. The model is also robust to the choice of environmental variables that will be included in the inefficiency equation provided that the spatial distance measure substantially captures the efficiency-enhancing factors. The average of estimated technical efficiency is 0.86. The growth in technical efficiency of 1-2% per year is explained by the slow adjustment process in the operation of the cooperatives lacking the medium to feedback production outcomes in the previous year to their operation cycle in the following year. Medium-sized cooperatives need to organize for strategic competitive advantage and to facilitate attainment of production efficiency.

JEL Classifications: C21, C23, C51, D24

Keywords: stochastic frontier, technical efficiency, electric cooperative, spatial externalities

[*]**Corresponding author,** Philippine Institute for Development Studies, Rm. 311 NEDA sa Makati Building, 106 Amorsolo St., Legaspi Village, Makati City, Philippines.
Tel. No.: +63 2 893 95 85 to 92 loc 3112; Fax. No.:+63 2 816 10 91; *E-mail addresses:* rlavado@mail.pids.gov.ph, rlavado@gmail.com

1. Introduction

Growth among developing countries is characterized by a dynamic landscape of evolving structure of output. While the agriculture sector used to dominate the output, industry and services is becoming a common feature of growth and development. The expansion of these sectors requires substantial infrastructure development especially among the isolated rural areas. One crucial component of these infrastructure development packages includes the utility sectors, electricity specifically.

While development assistance usually adopts a fairly comprehensive package, sustainability of some projects are at risk due to lacking sense of ownership among stakeholders/users. Sustainability of infrastructure usually involves community organizing and substantial advocacy campaign to stimulate the concept of ownership among the stakeholders. This strategy usually results to stakeholder who are willing to contribute for the maintenance of the project and leading towards sustainability. Electricity generation in rural Philippines is usually operated and maintained by users who group themselves as cooperatives and function like a small- to medium-scale enterprise. Electric cooperatives had been actively integrated in the power generation process in the Philippines and yet, problems of supply and demand imbalance sometimes reaching crisis level happened. What could have possibly triggered for these problems to happen?

Electricity is a peculiar commodity in the market because foremost, it cannot be stored, demand fluctuates depending on the time of day and season, and supply is subject to random losses. Despite these difficulties, producers have to make sure that the balance between supply and demand is sustained primarily to protect the consumers and ultimately to fuel development. This balance depends on how producers manage the vertically integrated stages of electricity production.

There are five vertically related stages of electricity supply production, namely, (1) supply of energy inputs, (2) generation, (3) transmission, (4) distribution, and (5) supply to final customers (Armstrong, Cowan and Vickers, 1994). Common energy inputs are fossil fuels such as coal and gas, nuclear fuel and renewable energy sources such as hydropower and solar energy. With the exception of renewable sources, energy fuels involve resource depletion and environmental costs. Generating electricity from these sources entails huge capital where investment costs are sunk. The amount of capital outlay differs from one energy source to another. Transmission and distribution of generated electricity are also very expensive and are natural monopolies since grid interconnection is needed and construction of two lines on one area will be inefficient. To be able to maintain the supply and demand balance throughout the system, a close coordination between the generation and transmission sector is necessary. This is primarily the reason why these two stages are typically vertically integrated. After passing through the distribution network, electricity is retailed to final consumers. Electricity retailers are the ones who buy bulk power from generators, market them to consumers, then bill and collect payments from them.

The Philippine government since the late ‘80s is burdened with huge fiscal deficits and foreign debt payments so that maintenance investment and financing for new power projects were not prioritized. After years of political turmoil in the early 1980s, the Philippine economy was once again severely affected by a power crisis in 1989 to 1993. With black-outs lasting 4 to 12 hours per day (Navigant Consulting, UPecon Foundation and Ian Pope & Associates, 2000), the crisis caused economic losses amounting to 600 to 800 million dollars per year or almost 1.5 percent of GDP (Navigant Consulting, UPecon Foundation and Ian Pope & Associates, 2000). The main reasons for capacity deficits were identified as: (1) inefficient maintenance of aging power plants; (2) rapidly declining hydropower plants; (3) delays in planned base-load power generation projects; and (4) shutting-down of the 620 MW Bataan Nuclear Power plant for safety and political reasons in 1986, without any provisions for a substitute. Table 1 shows the number of days with some brownout, energy sales, and megawatt per day lost.

[Table 1 here]

Private-sector investments were mobilized to address capacity deficits promptly. The generation monopoly of the National Power Corporation (NPC), a government-owned and controlled company responsible for power generation and transmission, was dissolved in 1987. Private sector investments were encouraged with the passage of the Build-Operate-Transfer (BOT) Law (RA 6957) of 1990 and the Emergency Power Crisis Act (RA 7648) which gave the president authority to speedily approve power procurement contracts with private suppliers, also known as independent power producers (IPP). In 1992, the

Department of Energy (DOE), which was previously dissolved, was recreated to plan and manage the development of the energy sector, this resulting to the surge of private sector participation in the power sector. By the end of 1994, the private sector has sponsored 2,194 MW of additional power plants.

Electricity consumption in the Philippines more than doubled from 16,433 GWh in 1981 to 42,412 GWh in 2000. This is equivalent to an average annual growth rate of 4.4 percent. The growth was led by residential consumption which grew at 7.4 percent. Industrial and commercial electricity consumption grew at 2.4 percent and 6 percent, respectively.

The main sources of residential electricity are the distribution utilities (DU) and the electric cooperatives (EC). In 1997, 56.3 percent of households sourced their electricity from ECs compared to 43.7 percent of DUs. However, ECs accounted for only 27 percent of residential electricity sales, 73 percent of which were sold by DUs. Of this, MERALCO, the utility serving the National Capital Region, provided 61 percent of all electricity supplied to the residential sector while other DUs provided only the remaining 12 percent.

Stochastic frontier analysis is one prominent methodology in analyzing the efficiency of production. The main advantages of SFA are the ability to account for noise, conduct test of hypothesis and the feasibility of incorporating the effects of environmental variables. Location specificities of efficiency-inducing conditions as well as the learning curve of technological adoption over time cannot be ignored. Hence, it is imperative to consider spatial and temporal dimensions in the analysis of production efficiency. An empirical assessment of the production efficiency of electric cooperatives in the Philippines is explored in this paper, taking into account spatial and temporal dependencies.

2. Electric Cooperatives in the Distribution Sector

Distribution utilities own and operate a system of wires and other sub-transmission assets that transfer electricity from transmission grid to end-users. The distribution sector in the Philippines is composed of one large private utility operator, 16 privately owned utilities, 7 municipal systems and 119 member-owned rural electric cooperatives (ECs). Given the difficulty of setting-up major grids in a country composed of thousands of islands, the ECs were formed to take charge of missionary electrification. More than half of all the households in the country (56.3%) source their electricity from ECs. These cooperatives, however, accounted for only 27% of total residential electricity sales. Moreover, majority of industrial and commercial companies source their energy from privately owned utilities.

These electric cooperatives usually have zero equity, plagued with high debt-service costs and its incentive to reduce system losses is very marginal. Limited resources resulting to captivity of consumers of these ECs further results to monopoly of franchise to deliver electricity within their service territories even with the deregulation. Thus, even if the law stipulates open access to the distribution sector, the ECs are undergoing rate regulation by the regulatory commission. If regulation is not undertaken, it is possible that distribution utilities could raise the rates above what they would be in a competitive market, raising the problem of determining proper rates for the delivery of electricity at the local level. Prices should be high enough to guarantee the viability of regulated firms; at the same time, prices should not be set too high to cause welfare losses. Because of asymmetric information, the regulator does not know the firm's true costs. High costs may be due to the firm's particular production situation or just because of its inefficiency.

3. Efficiency Analysis with Stochastic Frontier Analysis

SFA started with the stochastic frontier production function proposed independently by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977). They originally specified a production function for cross-sectional data with an error term split into two components, one to account for random effects and another to account for technical inefficiency. The model is expressed in the following form:

$$Y_i = x_i\beta + (v_i - u_i) \qquad i=1,...,n, \tag{1}$$

where Y_i is the logarithm of the production of the *i-th* firm;

x_i is a $k \times 1$ vector of (transformations of the) input quantities of the *i-th* firm;

β is an vector of unknown parameters;

v_i are random variables assumed to be iid $N(0,\sigma_V^2)$, and independent of u_i a non-negative random variables that accounts technical inefficiency in production, often assumed to be iid

$N^+(0,\sigma_U^2)$. The choice of appropriate transformation depends on the production function adopted.

The method requires specification of a cost or production function involving assumptions about the firms' production technologies. A symmetric error term v_i is then added to the random error term u_i to account for noise. Thus, the SFA method reduces reliance on measurements of a single efficient firm which is often the problem in other methods like Corrected Ordinary Least Squares (COLS) and Data Envelopment Analysis (DEA). However, accounting for stochastic errors requires additional specification of a probability function for the distribution of the errors and distribution of inefficiencies (e.g. half normal or truncated normal) thus, results depends on the assumptions imposed. Another drawback of the method is that even if there are no errors in efficiency measurements, there is a danger that some inefficiency may be wrongly regarded as noise (Hattori, Jamasb and Politt, 2002).

4. Efficiency of the Electricity Generation Sector

There are a number of empirical benchmarking studies that focus on the electricity industry. Most of the studies are primarily concerned with economies of scale and density (e.g. Salvanes and Tjotta, 1994) or the effect of the ownership form on utility efficiency (e.g. Kumbhakar and Hjalmarsson, 1998). This section will present some empirical studies on the relative efficiency of the distribution sub-sector of electricity utilities. Most of the efficiency studies focus on the relative efficiency in a single country while some adopt a cross-country focus.

Neuberg's (1977) was one of the earliest researches on the relative efficiency of electricity distribution. The study focused on the comparative efficiency of distribution firms that are privately owned versus those that are publicly owned, and investigated returns to scale in distribution using a 189-member full cross section of investor-owned utilities and a 189-member sub-cross section (from 529-member full cross section) of municipally owned electric utilities in 1972. Electricity distribution activities are defined to include load dispatching, customer installations, equipment maintenance, customer accounts activities including meter reading and billing, sales activity, and administration. The distribution returns to scale appear to be increasing, but not over the entire output range, and that the publicly owned utilities were not significantly less efficient than privately owned utilities.

Weyman-Jones (1992) used DEA for twelve Area Electricity Boards (AEBs) in the UK in 1986-87. While five are in the frontier, there is a wide divergence among the AEBs. Burns and Weyman-Jones (1996) used SFA, in studying the Regional Electricity Companies (RECs) in the UK, observed a significant but small cost-inefficiency and evidence of some economies of scale.

Salvanes and Tjotta (1994) investigated returns to scale (RTS) and returns to density (RTD) in Norwegian electricity distribution. Using data from 91 publicly owned distributors in 1988, a translog short-run cost function was specified to estimate the frontier. Results indicated that there was limited scope for scale improvements. However, there were unrealized returns to density, i.e., efficiency could be improved by supplying more electricity to each customer. It was also noted that environmental factors such as topography, climate, rural or urban location, and load factor may influence costs. When load factor and topography variables are in the cost function, however, these factors do not have a significant effect on efficiency.

Kumbhakar and Hjalmarsson (1998) applied DEA and SFA methods in a study of distribution utilities in Sweden between 1970 and 1990. They found evidence of economies of scale, technical progress, and relative efficiency of private utilities.

Filippini and Wild (2001) estimated an average-cost function for a panel of 59 Swiss local and regional electricity distribution utilities as a basis for yardstick regulation of distribution-network access prices. A multivariate average-cost function that can be employed by the regulatory commission was estimated to benchmark network access prices at the distribution level. The cost function specification includes several environmental variables to capture the heterogeneity of the service areas. Regional differences of the service areas, e.g. area shares of forests, agricultural areas or unproductive land and population density, significantly influence electricity distribution costs.

Pollitt (1995) investigated the relationship between efficiency and ownership, particularly, whether privately owned electric utilities are more efficient than those that are publicly owned. The section on distribution utilities includes a 1990 sample of 145 US and UK utilities and uses DEA and an average cost function. The study separates distribution utilities into small (firms with less than 300 employees), medium (firms with between 300 and 1,000 employees), and large (firms with more than 1,000 employees) samples in order to increase the likelihood that utilities are compared with similar firms and to provide less variation in DEA scores across the sample. Purchasing Power Parity rates are used to convert the operation and maintenance costs and wages into a single monetary unit. Results of the study do not show strong evidence that ownership affects performance of utilities. The study also suggests that RECs in the UK prior to their privatization were not less efficient than US distribution utilities.

Filippini (1998) used translog econometric (SFA and COLS) models for Swiss and New Zealand distribution utilities and found economies of scale. Among the policy suggestions in his study is a recommendation for mergers among the utilities.

Zhang and Bartels (1998) constructed separate DEA frontiers for electricity distribution in Australia (NSW and Queensland), New Zealand, and Sweden, having 32, 51, and 173 observations, respectively. The paper aimed to illustrate the effect of sample size on mean technical efficiency measures derived from DEA studies. Simulation showed that as sample size increases, the estimated mean technical efficiencies decrease generally. The rates of decrease also depend on the sample size. When sample size is small the rate is high, and when sample size is large the rate is low.

IPART (1999) reports a cross-country study sponsored by a regulatory agency that examined the relative efficiency of 6 distribution utilities in New South Wales, Australia using a sample of 219 utilities from Australia, England and Wales, New Zealand, and US from 1995 to 1998. The IPART study is an international benchmarking sponsored by the New South Wales (NSW) regulatory agency in Australia. The efficiency scores are calculated using a DEA-CRS model based on the argument that distribution utilities have no control over the scale of their operation. Operating expenses are converted from national currencies into a single monetary unit using Producer Purchasing Power Parities. The study estimates that the NSW utilities are, after adjustment of efficiency scores for the effect of environmental factors, between 13 and 41 percent less efficient than the frontier firms.

Jamasb and Politt (2001) reported an efficiency analysis of 63 European electricity distribution utilities to assess the potential of, and issues involved in, the use of cross-country analysis as input in incentive regulation process. Their sample includes utilities from the UK, Norway, Netherlands, Portugal, Italy, and Spain. The study uses DEA, SFA, and COLS methods with different model specifications to a set of data from 1997-1998. The mean values of efficiency scores of UK firms calculated with different methods and models are closer to the sample mean. The efficient frontiers, however, are dominated by smaller utilities than the UK firms. Consistent to Burns and Weyman-Jones (1996), the study also indicates that there are significant performance variations among the UK firms.

Hattori (2002) conducted a U.S.-Japan comparison of performance of electric distribution utilities from 1982 to 1997 using SFA to estimate the technical efficiency of the utilities. He specified a translog multiple-input distance function to model the technology of electricity distribution, also taking into account environmental influences in the analysis of technical efficiency. After controlling for environmental factors, the Japanese utilities are found to have been more efficient on the average. However, some the most efficient utilities in the U.S. have not always been less efficient than the most efficient utility in Japan. He also noted that inefficiencies in electricity distribution services have possibly been increasing over time, particularly in Japan.

5. Issues in Efficiency Estimation

Benchmarking studies on distribution utilities have adopted varying methods and a wide range of input and output variables. There is no consensus as to how the basic functions should be modeled, despite the fact that the technologies and characteristics of the distribution utilities are relatively similar. As in the case of distribution lines, some studies used it as input while others used it as output variable. Nevertheless, the inputs and outputs used in previous studies can give an indication of which of the variables are more widely chosen. Jamasb and Pollitt (2001) reviewed the frequency by which different input and output variables are used, noted that the most frequently used inputs are operating costs, number of employees, transformer capacity, and network length while the most widely used outputs are units of energy delivered, number of customers, and the size of service area. However, as pointed out by Kumbhakar and Hjalmarsson (1998), length of distribution lines that measures the amount of capital in the form of a network, has to be treated with caution because it can be misleading since it can reflect geographical dispersion of consumers rather than differences in productive efficiency. Therefore, in previous studies of relative efficiency differences, network capital was treated either as an output or as input but only after controlling for geographical dispersion. Exogenous variables specific to each utility have an important effect on efficiency scores. In the case of electric cooperatives, service area and number of actual billed customers are exogenous operating characteristics of each of the cooperative's environment, both of which encapsulate consumer density which accounts for geographical dispersion. The idea is that customer density should capture the effect of demographic features, in the sense that higher values of this variable can be expected to enable a firm to deliver more output per unit of input. For similar reasons, measurement of the effect of delivering energy at different voltages required by different customers is also needed, and therefore the proportion of total energy delivered that is distributed to residential customers is included as an additional operating characteristic (Estache, Rossi and Ruzzier, 2004). Finally, system loss and maximum demand on the system as measured by peak load are included as environmental input variables to account for technological differences among cooperatives in delivering electricity.

Kalirajan (1981) and Pitt and Lee (1981) incorporated the environmental variables in a second stage regression using the efficiency score obtained in the first stage as dependent variables. This method, however, has been criticized as inconsistent—in the first stage it was assumed that efficiency scores are independent and identically distributed while the second stage debunked this assumption (Kumbhakar, Ghosh, and McGuckin, 1991). To address this deficiency, Battese and Coelli (1995) proposed a time varying inefficiency model where both production and environmental variables are modeled in one stage.

6. Spatial Temporal SFA Model

Following similar specification as Reifschneider and Stevenson (1991), the proposed spatial-temporal stochastic frontier model is

$$\ln y_{it} = \ln f(x_{it};\beta) + v_{it} - u_{it}$$

$$v_{it} = \rho v_{it-1} + \psi_{it} \tag{2}$$

$$u_{it} = \frac{1}{1+\exp[-(w_{it}\gamma + z_{it}\phi)]} + \varepsilon_{it}$$

where, the subscript *i* refer to the electric cooperative and *t* the time period, hence, y_{it} is the output of cooperative *i* at time *t*, x_{it} are the factors of production, v_{it} is the autocorrelated (order 1) pure error, u_{it} are measures of inefficiency, w_{it} are measures of spatial distance, z_{it} are other environmental variables, ε_{it} and ψ_{it} are white noise terms, β, γ, ϕ, and ρ

are the corresponding parameters.[1] The production structure is assumed to be constant over time, hence reflected in time-independence of β. The temporal dependence measured by ρ also assumes homogeneity across cooperatives. The short-term dependency in efficiency indexed by ρ is not expected to exhibit structural changes within a short panel. The model is estimated using a hybrid of backfitting and maximum likelihood method similar to Landagan and Barrios (2007).

7. The Data and Model Specification

The data comes from all 119 electric cooperatives in the Philippines from 1990 to 2002 as compiled in the NEA database. Service area is measured by National Electrification Administration (NEA) as number of municipalities and *barangays* (smallest political unit) energized. Thus, total service area is derived by identifying the land area covered by each of the cooperative's franchise based on the Rural Electrification Chronicle (NEA, 1999). The total operating and maintenance expenditure is expressed in deflated values (1994=100) using the consumer price index for Fuel, Light and Water.

[1] In the absence of efficiency enhancing factors (w_{it} and z_{it}), it is assumed that technical efficiency will be normally distributed so that half of the firms are efficient and half are inefficient. Thus, when w_{it} and z_{it} are equal to zero, technical efficiency (u_{it}) is equal to ½.

NEA also does a classification and categorization of cooperatives. Cooperatives are classified based on their respective sizes as measured by circuit km of lines, total sales and residential connections, into extra large (EL), large (L), medium (M) and small (S).

The following groups of environmental variables are used:

Group 1: Total number of customers, residential customers, non-residential customers, service area, peak demand, system loss, purchased electricity, consumption density (kWh sales/number of customers), connection density (number of connections/service area), customer density (number of connections/transformer capacity).

Group 2: Since total number of customers is the aggregate of residential and non-residential customers, it is removed from Model 1.

Group 3: All absolute counts of customers are removed from Model 1.

Group 4: Considers only the following indicators: service area, peak demand, system loss, consumption density (kWh sales/number of customers), connection density (number of connections/service area), customer density (number of connections/transformer capacity).

Group 5: Considers the following indicators: total number of customers, service area, peak demand, consumption density (kWh sales/number of customers), connection density (number of connections/service area), customer density (number of connections/transformer capacity).

Group 6: Considers the following indicators: service area, peak demand, consumption density (kWh sales/number of customers), connection density (number of connections/service area), customer density (number of connections/transformer capacity).

The models fitted all assume the Cobb-Douglas production structure using the same set of production inputs. Different sets of environmental variables are used following the groupings above. The basic model fitted is

$$\ln y_{it} = \boldsymbol{\beta}'\mathbf{x}_{it} + e_{it} - u_{it} \qquad (3)$$

The production function estimates is presented in Table 2.

[Table 2 Here]

The time invariant panel data model assumes that the inefficiency term follows a truncated normal distribution and is constant over time within the panel ($u_{it} = u_i$). The time-varying decay model specification of Battese and Coelli (1992) is also fitted following inefficiency equation $u_{it} = u_i \exp[\delta(t-T)]$, where u_i is truncated normal and T is the most recent time in the panel. For both models, the environmental variables are added into the production function.

The spatial-temporal stochastic frontier defined in the previous section is also fitted and compared to the time-invariant and the time-decaying (Battese-Coelli) models. The measures of spatial distance were based on the average output in each neighborhood. Three neighborhoods were defined: region (biggest political sub-division of the country), province (second biggest political sub-division), and the cooperative classes defined above.

Spatial dependency of efficiency among spatially contiguous units can be explained by similarity in topographic and environmental conditions. Fiscal conditions and resource availability (following some spatial distribution, e.g., high household density areas that are usually contiguous own longer transmission lines) will define spatial dependence among cooperatives in the same classes. Details of variable definitions are given in Appendix 1.

8. Results and Discussions

The estimated technical efficiency coefficients from the time-invariant model, time-decaying model, and the spatial-temporal stochastic frontier models for panel data are compared. The discussion is followed by an analysis on how the efficiency of electric cooperatives behaves over time and space in the context of a spatial stochastic frontier model.

8.1 Estimated Technical Efficiency

The estimates of technical efficiencies from the three models and using 6 groups of environmental variables are summarized in Tables 3-7.

[Table 3 Here]

[Table 4 Here]

[Table 5 Here]

[Table 6 Here]

[Table 7 Here]

Convergence in the estimation of the Battesse-Coelli model is affected seriously by the multicollinearity present among the environmental variables. While the estimation were properly implemented both in the time-invariant panel model and in spatial-temporal stochastic frontier model, Battese-Coelli did not converge where Groups 1, 3 and 5 (cases of severe multicollinear variables) of environmental variables are included.

Among the three models, Batesse-Coelli also produced the highest estimates of inefficiency. Estimate of inefficiency from the spatial-temporal stochastic frontier model averages 20%, 30% from the time-invariant panel model, up to 85% in Battesse-Coelli model. The literature on stochastic frontier models in fact noted the severe underestimation of technical efficiency among maximum-likelihood based estimation procedures. This seems to have been resolved in the hybrid of backfitting estimation used in spatial-temporal stochastic frontier model.

Estimates of technical efficiencies from the spatial-temporal stochastic frontier model are also more stable than those generated from the time-invariant and time-decaying models. The inclusion of spatial dependency indicator could have contributed in the stabilization of the technical efficiency estimates. A possible source of variation is aptly identified in the spatial-temporal stochastic frontier model that is not done in both the time-invariant and the Battesse-Coelli models.

The spatial-temporal stochastic frontier model also exhibited robustness to the group of environmental variables used to explain inefficiency. Tables 3-5 exhibit similar profile for each group of environmental variables. This is further supported by strong correlations among the technical efficiencies from each of the 6 groups. This robust behavior will facilitate the use of the model since selection of appropriate environmental variables will be a constraint in modeling. The choice of appropriate spatial neighborhood should be carefully planned since this will seriously affect the estimates of technical efficiency. The spatial neighborhood should be chosen so that it will serve as a proximate indicator of source of technical efficiency/inefficiency.

8.2 Spatial Dependencies of Technical Efficiency

Transformer capacity and distribution capacity are overlapping indicators for capital. For better interpretation of the production and technical efficiency equations, transformer capacity was removed from the production function.

A province is composed of a few electric cooperatives. A region is composed of several geographically contiguous cooperatives which are not necessarily related in the context of efficiency. Cooperative classes are defined in terms of efficiency targets of the regulatory agency (NEA). In defining the neighborhood system, region does not provide a conditionally significant spatial effect, a possible consequence of heterogeneity in efficiency among cooperatives in the same region. There is a significant spatial dependency using provincial average output as a measure of spatial distance. This is also true using cooperative classes as basis in the definition of a neighborhood, used in subsequent discussions.

Outputs of electric cooperatives are more sensitive to the labor inputs than capital represented by the length of their distribution lines. Labor significantly contributes in the production function ($p<0.000$) while capital does not ($p<0.367$). Over the panel of 12 years, there are no significant changes in the length of transmission lines while labor vary significantly among the cooperatives. It may also be taken to mean that optimal output can still be achieved by the electric cooperatives through strategic optimization of labor inputs.

Conditional on the production function, spatial dependency among cooperatives can significantly explain technical efficiency ($p<0.003$). The regulatory agency defined the classes based on the points they generated from the indicators of efficiency (distribution lines, total sales, and residential connections). Thus, cooperatives in the same class exhibited similar efficiency level resulting to a significant coefficient of the spatial neighborhood indicator.

The significance of spatial externalities ($p<0.003$) provides a viable strategy of managing electric cooperatives to facilitate the attainment of efficiency. Extra large cooperatives are the most efficient with average technical efficiency coefficient of 97.55% or an output off the maximum possible by 2.45% only. Large cooperatives however have an average technical efficiency coefficient of 89.67% or off by 10.33% of maximum output. Medium class cooperatives have average technical efficiency of 47.19%, off the maximum output by 52.81%. An implication identifies a strategic move for cooperatives in medium class to organize into federations to maximize their competitive advantage to achieve efficiency. Other environmental factors like number of customers, service area, peak demand, system loss, consumer density and consumption density are not conditionally significant. These factors constitutes the criteria in classifying cooperatives hence, spatial externalities indexed by cooperative classes will suffice to account for efficiency/inefficiency of electric cooperatives. In general, as the size of cooperatives increases, technical efficiency increases.

A properly chosen measure of spatial distance can explain most of the inefficiencies among the producers. This results to estimates of technical efficiency that is robust to the choice of environmental variables. Once the spatial distance indicator is identified, the choice of environmental indicators will no longer be an issue in modeling.

8.3 **Temporal Dependencies of Technical Efficiency**

There is a strong temporal dependency in the technical efficiency of electric cooperatives. From the annual data, the estimated autocorrelation coefficient (lag 1) is 0.89. This indicates the slow adjustment process among electric cooperatives in their production process. Random shocks that are not related to the labor and capital inputs cannot be easily mitigated and those that occurred in the previous year can still yield lingering effects in the following year and possibly in the next few more years. This may also reflect a myopic planning process among the cooperatives. The lack of an immediate feedback mechanism of the outcomes of production process in the previous year to the plans and targets of the following year results to the large autocorrelation among the residuals. This is further supported by the slow growth in estimates of technical efficiency by 1-2% a year from 1990 to 2002.

9. Conclusions

A stochastic frontier model that accounts for spatial externalities and some environmental variables in the efficiency/inefficiency equation is used in characterizing efficiency among electric cooperatives in the Philippines. The model mitigates underestimation of technical efficiency coefficients from maximum likelihood-based procedures.

Within the estimation period (1990-2002), technical efficiency is estimated at 0.86 or inefficiency of about 14%. While the 'extra large' are nearing frontier production levels with technical efficiency of 0.98, those cooperatives classified as 'medium' by the regulatory agency yield an average technical efficiency of 0.47, still too far away from frontier production level. This explains the persistent electricity supply problems in many rural areas in the Philippines.

Spatial externalities index by a distance measure into the inefficiency equation will suffice to account for environmental factors that can potentially influence production efficiency of electric cooperatives. Modeling is robust to the choice of environmental variables provided that a spatial distance measure is aptly identified. In the context of electric cooperatives, the spatial distance need not be based on contiguity alone.

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Appendix 1: Description of Variables

Variable Names	Definition
ltotalkWhsales	logarithm of total kWh sales calculated as total sales minus sales to other electric companies
llabor	logarithm of the number of employees employed by each cooperative
ltrans	logarithm of transformer capacity in kVA based on the transformer capacity rating for each cooperative
ldist	logarithm of distribution capacity measured in total circuit km lines
Total number of customers	total number of customers connected to each cooperative, measured as the sum of different types of customers disaggregated as residential, commercial, industrial, public building, street lights, large road, irrigation, BAPA, water system, wholesale to sister cooperative, and others
Residential customers	total number of residential customers
Non-residential customers	total number of commercial and industrial customers, as well as public building, street lights, large road, irrigation, BAPA, water system, wholesale to sister cooperative, and others
Service area	as the total land area of each cooperatives' mandated franchise area in square kilometers
Peak demand	peak demand capacity of each cooperative in kilowatts
System loss	system losses of each cooperative (due to pilferage, leakage, and others)
Purchased electricity	the amount of electricity purchased by the cooperative from NPC or sister cooperatives
Connection density	defined as the number of customer divided by the service area of cooperatives
Customer density	defined as the number of customers divided by transformer capacity
Consumption density	defined as sales of electricity divided by the number of customers

Table 1 Power Outages in Luzon Grid

YEAR	Days with brown-out	Energy sales lost (in gWh)	Energy sales lost (in kWh per day)
1980	145	125	862
1981	90	66	733
1982	148	156	1054
1983	70	130	1857
1984	16	42	2625
1985	8	11	1375
1986	16	18	1125
1987	28	27	954
1988	12	6	500
1989	41	91	2220
1990	103	251	2437

Sources: National Power Corporation, as cited in World Bank Country Report, April 1993; Fabella, 2002.

Table 2. Production Function Estimates

	Coefficient	Standard Error	t-value
log labor	1.0147	0.0537	18.89
log transformer	0.4361	0.0232	18.76
log distribution	0.3803	0.0264	14.40
constant	-1.8932	0.2980	-6.35
	R-sq		
	within	0.5781	
	between	0.8436	
	overall	0.8017	
	Number of Obs	1354	

Table 3. Technical Efficiencies from Time Invariant Panel Data Model

Environmental Variables	Mean	Std. Dev.	Min	Max
Group 1	0.754565	0.169848	0.283783	0.975371
Group 2	0.707428	0.155556	0.303192	0.954478
Group 3	0.669146	0.16112	0.286933	0.945696
Group 4	0.662221	0.162328	0.283509	0.945089
Group 5	0.762548	0.164745	0.298508	0.976912
Group 6	0.686618	0.160136	0.315796	0.951795

Table 4. Technical Efficiencies from Time-Decaying (Battese-Coelli) Model

Environmental Variables	Obs	Mean	Std. Dev.	Min	Max
Group 1	*Convergence not achieved*				
Group 2	1252	0.276538	0.147955	0.008762	0.679455
Group 3	*Convergence not achieved*				
Group 4	1252	0.170208	0.0949	0.005634	0.426347
Group 5	*Convergence not achieved*				
Group 6	1252	0.141498	0.078125	0.004954	0.354655

Table 5. Technical Efficiencies from Spatial-Temporal Stochastic Frontier Model

(Region as Basis for Neighborhood Definition)

Environmental Variables	Mean	Std. Dev.	Min	Max
Group 1	0.802886	0.256727	0.36794	1
Group 2	0.800048	0.258276	0.367897	1
Group 3	0.80431	0.258681	0.367889	1
Group 4	0.807176	0.256038	0.368417	1
Group 5	0.806146	0.256015	0.368189	1
Group 6	0.805801	0.256196	0.368454	1

Table 6. Technical Efficiencies from Spatial-Temporal Stochastic Frontier Model

(Province as Basis for Neighborhood Definition)

Environmental Variables	Mean	Std. Dev.	Min	Max
Group 1	0.806241	0.257404	0.367882	1
Group 2	0.80614	0.257874	0.367891	1
Group 3	0.80858	0.256739	0.367967	1
Group 4	0.808527	0.256286	0.367972	1
Group 5	0.806284	0.256385	0.367961	1
Group 6	0.8029	0.25862	0.367939	1

Table 7. Technical Efficiencies from Spatial-Temporal Stochastic Frontier Model

(Cooperative Class as Basis for Neighborhood Definition)

Environmental Variables	Mean	Std. Dev.	Min	Max
Group 1	0.814843	0.249719	0.367966	1
Group 2	0.81527	0.248157	0.36816	1
Group 3	0.818887	0.248672	0.368135	1
Group 4	0.817403	0.251005	0.367936	1
Group 5	0.817507	0.24856	0.368583	1
Group 6	0.814996	0.250781	0.368095	1