A Spatial Econometric Model for Household Electricity Consumption in the Philippines

Abstract

While electricity is regarded as a catalyst for economic development, twelve million Filipinos still do not have access to electricity. Most of the studies relating to energy focused on socio-demographic and economic context. This study seeks to propose a new perspective in the Philippine's household electricity consumption by incorporating space. To determine this, three spatial econometric models were considered: Spatial Error Model, Spatial Lag Model, and Spatially Lagged X model. The result of several model specification tests led to the conclusion that the household electricity consumption in the Philippines exhibits spatial autocorrelation. Spatial Lag Model (SLM) with a spatial distance weight of 150 km is the most appropriate model for the study. The study shows that by decomposing the result of the Spatial Lag Model, a direct effect of Human Development Index, concrete national road, urban population, high electricity cost and low voltage on household's electricity consumption was observed.

INTRODUCTION

The geography of the Philippines, consisting of 7,641 islands (1) and of remote communities raises unique challenges in terms of accessibility and security to basic services, such as electricity. Energy infrastructures are frequently affected by tropical storms and seasonal variation due to the country's topography (2). While electricity is regarded as a catalyst for economic development (3), twelve million Filipinos still do not have access to electricity (4). The nation's pressing problems such as growing population, climate change, changing consumption patterns and even rapid economic development have their own influence on electricity demand. (5).

A considerable number of studies have been conducted to analyze the household electricity consumption using several approaches. These methods include Regression analysis (6,7,8,9,10,11), Input-output analysis and structure decomposition analysis (12), Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) model (13) ,Probit models (14), and Floor Area Ratio Model (15). The said studies, however, are framed in the socio-demographic and economic context, and do not account for spatial influence. Conversely, just a fair number of foreign energy-related studies have been carried out using spatial approach. These spatial models include: Spatial Error Model (16) , Spatial ARIMA (17), Spatial autoregressive model with autoregressive disturbances (SARAR) (18), Spatial Durbin Model (19), Stochastic Frontier model augmented with spatial-temporal terms (20).

This study provides a new perspective in the Philippines household's electricity consumption by incorporating spatial dimension. This new approach could provide a more pragmatic perspective in analyzing household electricity to be used by policy-makers, and private sector for future initiatives and energy innovation.

The study aims to fulfill the following specific objectives: (1) To describe the relationship between four constructs: economic factors, household electrical factors, geographical factors, and household electricity consumption of the Philippine provinces for the year 2011. (2) To determine if there is a spatial dependence in the Philippine's household electricity consumption and to quantify if such dependency exists. (3) To compare possible models that can explain the condition of household electricity consumption in the Philippines using the following: Ordinary Least Squares Regression (OLS), Spatially Lagged Y Model (SLM), Spatial Error Model (SEM), and Spatially Lagged X Model (SLX).

MATERIALS AND METHODS

The study consists of information gathered from 74 provinces in the Philippines. Due to inaccessibility of several data, the provinces of Basilan, Lanao del Sur, Maguindanao, Sulu, Tawi-Tawi and Zamboanga Sibugay were excluded from the study. The main data was obtained from the Household Energy Consumption Survey (HECS) 2011 dataset acquired from the Department of Energy. Missing values were addressed using Predictive Mean Matching (PMM), one of the built-in imputation models of Multivariate imputation by chained equations (MICE). For the purpose of this study, imputation method was computed by province. To achieve estimate stability, five (5) iterations were employed.

Table 1. Variables considered in the Study

Independent variables			Dependent variable
Household electrical factors	Economic factors	Geographical factors	
Awareness of energy labeling program	Human development index	Landarea	Household electricity consumption (kWh) 2011
Brownout	Labor force participation rate	Concrete National Road	
Fluctuating voltage		Urban population	
High electricity cost	Young dependents		
Low voltage	Internal revenue allotment per capita		
Private investors owned utilities	Inflation rate		

The study made use of several statistical softwares such as Microsoft Excel, SPSS, R language and Geoda Software. Pearson correlation analysis was performed to determine the strength and direction of non-spatial relationship among the variables under study. Moreover, This study made a comparative analysis on the performances of four econometric models. Using the OLS model as the benchmark, four models were considered; classical OLS regression model, Spatial Error Model, Spatial Lag Model, and Spatially Lagged X model.

Spatial Error Model, assumes that the underlying data generating process / spatial covariate that induces spatial autocorrelation was not accounted in the model, thus the burden of spatial autocorrelation is given to the error term. (21)

$$= + u, whr\ u = \lambda u +$$

Where parameter $\lambda$is the spatial autoregressive coefficient that mirrors the interdependence between regression residuals; Wu represents the interaction effects among the disturbance term. is the error term such as $\rightarrow ii(0, \sigma^2 I_N)$.

Spatial Lag Model, postulates that the autoregressive processes of the model lies in the response variable, (22)

$$\boldsymbol{y} = \rho + \beta + \boldsymbol{\varepsilon}$$

$$\boldsymbol{\varepsilon} \rightarrow ii(0, \sigma^2 I_N)$$

Where, is the endogenous lag variable for the spatial weights matrix W; Rho (ρ) is the spatial autoregressive parameter that indicates the strength of interactions present between the observations of y. $\boldsymbol{y}$represents the dependent variable, is the spatial weights matrix; represents the observations on the exogenous variables, with an associated regression coefficient vector β.

Spatialy Lagged X Model, specifies that the spatial autoregressive processes rests in the exogenous variables. (22)

$$= \beta + \theta + \boldsymbol{\varepsilon}$$

Where **Y** represents an $\times 1$ vector consisting of one observation on the dependent variable for every unit in the sample$i = 1, .., N$. **X** denotes an $\times k$matrix of explanatory variables associated with the $k \times 1$parameter vectorβ, and $\boldsymbol{\varepsilon} \rightarrow ii(0, \sigma^2 I_N)$., matrix of exogenous lags, and θrepresents the spatial spillover effects

This study, applied distance-based spatial weight matrix to create a neighborhood structure which accounts for the archipelagic characteristic of the Philippines (150 km, 190 km, and 210 km). Row Standardization or the method of rescaling the row of the spatial weights matrix to sum to one was also employed to facilitate different model comparison. Moran's Index score, and Lagrange Multiplier (LM), and Local Indicator of Spatial Autocorrelation (LISA) were used in order to quantify the degree and to identify the kind of spatial dependence present in the model, latter test will identify the specific provinces that significantly contribute to such dependence. Ultimately, the final model shall be decomposed to characterize the spatial impact in the model.

RESULTS AND DISCUSSION

Correlation Analysis

Pearson correlation analysis was performed to determine the strength and direction of non-spatial relationship among the variables under study. The results from correlation analysis are presented in Table 1. In contrast with earlier findings (9), the variables High electricity cost, Awareness to Energy labelling program and Private Investor Owned Utilities (PIOUS) showed positive significant correlation to household electricity consumption per capita.

These finding provides supplementary evidence that Philippine's electricity demand in residential sector is inelastic due to limited alternative energy source for household use. The study may also infer that the government's energy labelling program may not be as effective in reducing the household electricity consumption. The PIOUs variable indicated that connection to main power grid may result to higher electricity consumption due to constant supply and higher amount of electric load provided by them compared to its Electric cooperative counterparts. Therefore, a significant increase in electricity consumption is expected. As anticipated the variables Low voltage and Fluctuating voltage exhibits significant but negative correlation with electric consumption per capita.

HDI revealed to have a strong correlation with electric usage per capita. This result is in line with the previous energy studies (11,23,24). In pursuit of higher paying jobs, better education, and better health care services, people tend to move from rural areas to urban cities, which in turn could translate into higher electricity demand (23)

A significant positive correlation was also observed between urban populations and electricity usage. This result is consistent with preceding energy studies (14,25,23,8). Conversely, a significant negative correlation was found between land area and electricity usage.

Table 2. Pearson Correlation Analysis Result

KWH per capita	Household Electrical Factors	Economic factors	Geographical Factors
Pearson correlation	Energy Labelling Program (0.51)*	Human Development Index (0.66)*	Land area (-0.25)*
	Private Investors Owned Utilities (0.63)*	Labor Force Participation rate (-0.40)*	Urban Population (0.58)*
	Fluctuating Voltage (-0.40)*	Young dependents (0.50)*	
	High Electricity cost (0.37)*		
	Low voltage (-0.30)*		

( ) Statistic value , * p-value < 0.05

Spatial Autocorrelation

Moran’s I and Local Spatial Autocorrelation (LISA) tests determined that the household electricity consumption in the Philippines exhibits spatial autocorrelation. Nearby provinces which exhibits similar characteristics was found within the distance of 150 km (Moran’s=0.1818 $p<0.005$), 190 km (Moran’s=0.1661, $p<0.005$), and 240 km (Moran’s= 0.08, $p<0.024$). (See table 3)

Table 3. Moran's Index and Local Spatial Autocorrelation (LISA)

Distance (Km)	Moran’s I	P-value	LISA-nonsignificant	Neighborless regions	LISA-significant
150	0.1818	0.005	50	Batanes , Palawan	22
170	0.1992	0.004	51	Batanes , Palawan	21
190	0.1661	0.005	47	Batanes , Palawan	25
210	0.1212	0.01	48	Batanes , Palawan	24
240	0.08	0.024	49	Palawan	24

After several specification tests, the distance metric 150 km exhibits the most favorable statistical result compared to other distance metrics with lowest Akaike Information Criterion (AIC=55.77) and the highest log likelihood (-19.886).

Distance weight: 150 kilometers

It can be observed in Figure 1 that the distance of 150 km yields a statistically significant Moran statistic of 0.1818 ($p<0.005$). The test revealed that majority (28%) of the provinces belong in upper-right (high-high) quadrant. This implies that majority of these provinces as well as their surrounding neighbors shares similar high electricity consumption per capita. Most of these provinces belong in Region 4-A and NCR region.

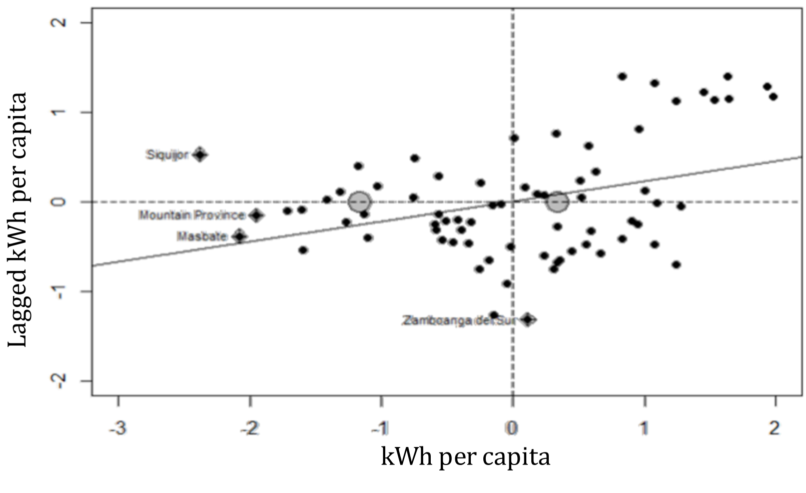

Figure 1. Moran’s I scatterplot: δ=150 km

Note: Neighborles provinces indicated by grey circle: Palawan and Batanes
Provinces with high influence measures are indicated by

Figure 2 illustrates the Local Indicator for Spatial Autocorrelation (LISA) significance map and cluster map of the household electric consumption per capita (δ=150 km). The significant provinces that belong in upper-right (high-high) quadrant are the following: Aurora, Bataan, Batangas, Bulacan, Cavite, Laguna, NCR, Nueva Ecija, Pampanga, Pangasinan, Rizal, Tarlac and Zambales. This implies that these provinces as well as its surrounding neighbors have high electric usage per capita. Biliran, Isabela, and Negros Occidental are the significant provinces that lie in the third quadrant (low-low), this denotes that these provinces together with their surrounding region have low household electric usage per capita.

Siquijor, however, is the only significant province that belongs in second (low-high) quadrant. This imples that Siquijor has low electricity usage while its surrounding neighbors have high electricity usage. Whereas, Aklan, Davao del Norte, Ilocos Norte, Ilocos Sur and Misamis Occidental are the significant provinces that belong in fourth quadrant (high-low values), this denotes that these provinces have high electric usage, its surrounding provinces, however, have low electric usage.

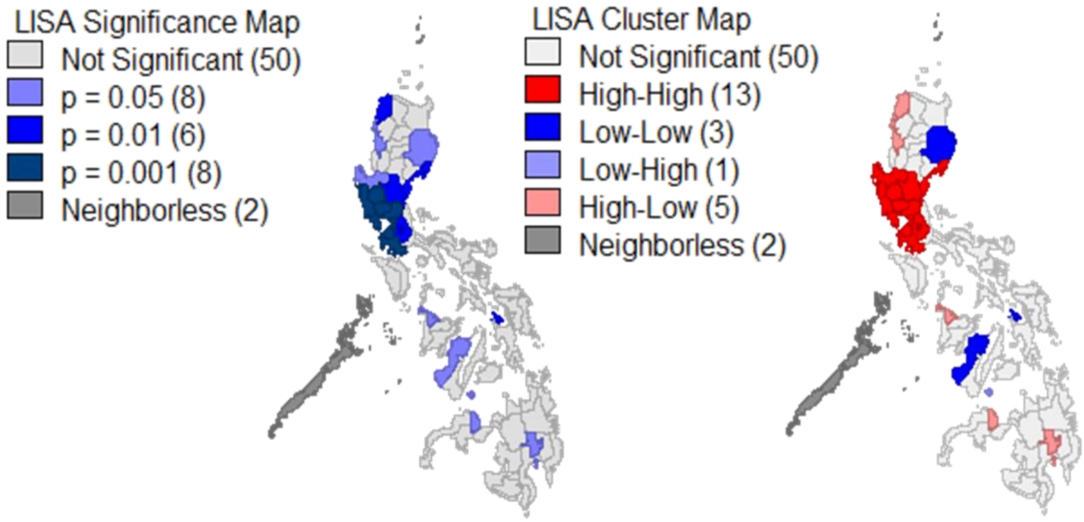

Figure 2. LISA Significance and Cluster Map: 150 km

Econometric models

This section presents the empirical result of the spatial econometric models. Household electricity kWh per capita (natural logarithm form) was used as the response variable. The explanatory variables of the initial model include: land area (sq km), concrete national road (natural logarithm form), urban population (natural logarithm form), human development index (2009), labor force participation rate 2011, young dependents 2010 (0-14 yrs old), internal revenue allotment per capita 2011, inflation 2011, number of household who are aware of the energy labeling program, proportion of households connected to PIOUS, proportion of household who encountered brownouts, proportion of household who encountered fluctuating voltage, proportion of household who encountered high electricity cost (natural logarithm form), and proportion of household who encountered low voltage. Correspondingly, 150 km row-standardized distance weight matrices were utilized as the spatial weight.

The results of the initial coefficient estimates of SLM (full model) is presented in Table 4, while Table 5 presents the empirical results of the reduced spatial lag model after eliminating the non-significant variables using backward elimination method.

Table 4. Spatial Lag Model (full model)

SLM FULL MODEL	150 KM	
COEFFICIENT	Estimate	P-value
(Intercept)	5.3125	0.0000
Land area	0.0000	0.7063
Concrete National Road (Natural logarithm)	0.2568	0.0106
Urban Population 2010 (Natural logarithm)	0.0872	0.0384
Human Development Index 2009	1.9020	0.000
Labor force participation rate	-0.0130	0.1431
Young Dependents	0.0000	0.6907
Internal Revenue per capita	0.0000	0.8538
Inflation	0.0181	0.4628
Awareness Energy Labelling	0.0000	0.8210
Private investors owned utilities	0.5010	0.0904
Brownout	0.1885	0.6376
Fluctuating voltage	-0.0608	0.8895
High electricity cost (Natural logarithm)	0.3272	0.0335
Low voltage	-0.5464	0.2046

Condition number: 81.051, Breusch-Pagan = 14.32 $p<0.488$

Table 5. Spatial Lag Model (reduced model)

SLM REDUCED COEFFICIENT	150 KM		Diagnostics	
	Estimate	P-value	Rho (ρ)	0.0862
(Intercept)	4.4812	0.000	Condition Number	24.1709
Concrete National Road (Natural logarithm)	0.2367	0.0124	Likelihood Ratio Test	4.2110 (0.0406)*
Urban Population (Natural logarithm)	0.1197	0.0004	Log likelihood	-19.8864
Human Development Index (2009)	2.3076	0.000	AIC	55.773
High electricity cost (Natural logarithm)	0.4463	0.0002	LM test for residual autocorrelation	2.4591 (0.1186)*
Low voltage	-0.5900	0.0046	Breusch Pagan	7.4027 (0.1935)*

( )*p-value <0.05

Table 6 presents the Lagrange Multiplier test, this analysis shall identify the kind of spatial autocorrelation processes present in the reduced model. The analysis found that the underlying data generating process are characterized by the following: spatial error (4.09, p<0.0441), spatial lag (4.13, p<0.0424), and spatial autoregressive moving average (6.7530, p<0.0352).

Table 6. LM diagnostic test with respect to the reduced model $= 150\ k$

LM	150 KM	P-value
LMerr	4.0939	0.0441
LMlag	4.1349	0.0424
RLMerr	2.6181	0.1073
RLMlag	2.6590	0.1034
SARMA	6.7530	0.0352

Model Comparison

Table 7 presents a comparative analysis of the reduced (spatial) econometric models: OLS, SLM, SEM and SLX. In order to identify the most appropriate (spatial) econometric model for this study, the AIC (Akaike Information Criterion), and the Log likelihood test served as a criterion for goodness-of-fit. As shown in Table 7, among the four models, the Spatial lag model has the lowest AIC (55.7730), and highest log likelihood (-19.886). Accordingly, rho (ρ=0.0862) or the added spatial effect variable in the model exhibits positive and significant effect to the model (likelihood ratio =4.211 p<0.041). The value for Breusch-Pagan test indicates that the four (4) models are free from heteroscedasticity.

Based on these tests, the researcher can now conclude, that Spatial Lag Model with a distance weight of 150 km is the most suitable model for this study.

Table 7. Comparative Analysis: Reduced Model Specification (150 km)

150 KM	Base Model: Non Spatial Regression via OLS		SLM		SEM		SLX
	Statistic	P-value	Statistic	P-value	Statistic	P-value	Statistic
ρ or λ		-	0.0862	-	0.3374	-	-
Condition Number	24.1709	-	24.1709	-	24.171	-	24.171
Likelihood Ratio Test	-	-	4.2110	0.0406	3.6979	0.0555	-
Log likelihood	-21.9919	-	-19.886	-	-20.143	-	-
LM test for residual autocorrelation		-	2.4591	0.1186	-	-	-
AIC	57.9838	-	55.7730	-	56.311	-	63.318
Breusch-Pagan value	5.9730	0.3101	7.4027	0.1935	6.0928	0.2986	-

Spatial Impact

The direct and indirect impact of the Spatial Lag Model with δ=150 km is presented in Table 8. The direct impact of increasing concrete national road is significant, suggesting that we would see increase in household electric consumption per capita in provinces which have longer concrete national road. This finding supplemented the study of Ojede et. al (19), the literature stated that efficient highway networks provide economic-social opportunities, and better accessibility to services, such as, electricity. This in turn could translate into higher electricity demand. The indirect effect of concrete national road, however, did not show any significance in the model.

Urban population also shows positive direct impact on electricity usage, this suggests that we would see increased in per capita household electric consumption in provinces which have higher urban population. Previous studies cited that rural to urban migration is one of the main factors that increases electricity consumption in urban areas (25,23). It was also mentioned that city residents less likely to acknowledge energy as a national concern compared to their rural counterparts, hence electricity consumption in urban areas is higher compared to rural areas (14). Likewise, it was pointed out that urban population is less responsive to electricity price changes compared to their rural areas (8). Conversely, the indirect effect of urban population did not show any significance, implying that increase in urban population on neighboring provinces will not affect electricity usage.

HDI yields positive direct effect on electricity usage, suggesting that we would see increase in electricity usage in provinces which have higher HDI levels. This result is in line with the previous energy studies (11,23,24). In pursuit of higher paying jobs, better education, and better health care services, people tend to migrate from rural areas to urban cities, which can lead into higher electricity demand (23,11). Niu et al. (11) cited that an improvement in quality of life changes household's electricity consumption demand. Starting from basic energy needs such as lighting and cooking to higher-level energy needs such as sanitation, and refrigeration.

Low voltage shows significant but negative effect on electricity usage. Finally, the variable, high electricity cost exerts a positive direct impact on electric usage, suggesting that we would see increased electric consumption in provinces with higher proportion of households which encounter high electricity cost. This finding, however, provides additional evidence that Philippine's electricity demand in residential sector is rather inelastic due to limited alternative energy source for household use.

Table 8. Direct, indirect and total effects

Impact	DIRECT		INDIRECT	
Variables	Estimate	P-values	Estimate	P-values
Concrete National Road (Natural logarithm)	0.2370	0.0114	0.0214	0.1548
Urban Population (Natural logarithm)	0.1199	0.0006	0.0108	0.0952
Human Development Index (2009)	2.3106	0.0000	0.2088	0.0762
High electricity cost (Natural logarithm)	0.4469	0.0002	0.0404	0.0704
Low voltage	-0.5907	0.0043	-0.0534	0.1247

CONCLUSION

The result of several model specification tests led to the conclusion that the household electricity consumption in the Philippines exhibits spatial autocorrelation. Spatial Lag Model (SLM) with a spatial distance weight of 150 km is the most appropriate model for the study.

In general, by decomposing the results of the spatial lag model, a direct effect of Human Development Index, concrete national road, urban population, high electricity cost and low voltage on household's electricity consumption was observed.

The large direct impact of HDI is consistent with the positive externality of HDI found in the economic literatures. Low voltage revealed significant but negative effect on electricity usage. Remarkably, the study also revealed that concrete national road generates more direct effect on electricity consumption than urban population. As anticipated, high electricity cost revealed a positive direct effect on electricity consumption. This finding provides further evidence that Philippine's electricity demand in residential sector is rather inelastic due to limited alternative energy source for household use.

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