Regionally-varying and Regionally-uniform Electricity Pricing Policies Compared across Four Usage Categories

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Abstract

The objective of our research is to predict how electricity demand varies spatially between *status quo* regionally-uniform electricity pricing and hypothetical regionally-varying electricity pricing across usage categories. We summarize the empirical results of a case study of electricity demand in South Korea with three key findings and their related implications. First, the price elasticities of electricity demand differ across usage categories. Specifically, electricity demands for manufacturing and retail uses were price inelastic and close to unit elastic, respectively, while those for agricultural and residential uses were not statistically significant. This information is important in designing energy policy, because higher electricity prices could reduce electricity demands for manufacturing and retail uses, resulting in slower growth in those sectors. Second, spatial spillovers in electricity demand vary across uses. Understanding the spatial structure of electricity demand provides useful information to energy policy makers for anticipating changes in demand across regions via regionally-varying electricity pricing for different uses. Third, simulation results suggest that spatial variations among electricity demands by usage category under a regionally-varying electricity-pricing policy differ from those under a regionally-uniform electricity-pricing policy. Differences in spatial changes between the policies provide information for developing a realistic regionally-varying electricity-pricing policy according to usage category.

Keywords: Elasticities of electricity demand, Regionally-varying electricity pricing, Spatial spillovers

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1. Introduction

1.1. Background

Many countries have addressed the need for electricity conservation in recent years, primarily for two reasons (Sahraei-Ardakani et al., 2012). First, global efforts to reduce greenhouse gas emissions (GHG) have underscored the need for cost-effective energy conservation (IEA, 2009). For example, the U.S. Environmental Protection Agency (NAPEE, 2009) has emphasized the economic value of energy efficiency via reducing carbon emissions in terms of achieving the potential for cost-effective energy efficiency. Second, due to rapidly growing energy demand by emerging economies and the extreme temperatures purportedly associated with recent global climate change, electricity conservation has been identified as a key response to excessive electricity demand (e.g., 2013 South Korea power crisis (AFP, 2013); 2012 India blackout (Reuters, 2012); Japan's electricity crisis since the 2011 Tohoku earthquake (Nakano, 2011); 2005 Java-Bali blackout (Donnan, 2005); 2003 Northeast blackout (CNN, 2003); 2003 Italy blackout (BBC News, 2003); California electricity crisis of 2000 and 2001 (Sweeney, 2002); and 1999 Southern Brazil blackout (The New York Times, 1999).

Research on efficient electricity supply and pricing systems is needed to help advance electricity conservation (Gillingham et al., 2009; Ryan and Campbell, 2012). This study focuses on developing an electricity-pricing system to promote electricity conservation. Previous research typically attempted to quantify the influence of price changes on electricity demand by estimating price elasticities of demand for different uses and regions (Bohi, 1981; Bohi and Zimmerman, 1984; Lin et al., 1987; Espey and Espey, 2004; Paul et al., 2009; Saunoris and

Sheridan, 2013). The heterogeneity across uses has been evaluated for manufacturing, agricultural, residential, and retail (mainly used for commercial buildings) uses (e.g., Bose and Shukla, 1999; Kamerschen and Porter, 2004; National Institute of Economic and Industry Research, 2007). Previous research commonly used linear regression and panel data, time series, and meta-data analyses to compare price elasticities across uses. The price elatisticies of manufacturing, agricultural, residential, and retail electricity demand range widely from –1.82 to 0.00, –2.39 to 0.152, –2.25 to 0.098, and –1.36 to 0.00, respectively (see Table 1).

Similarly, regional differences in price elasticities of electricity demand have been compared (e.g., Bernstein and Griffin, 2005; Fell et al., 2010; Paul et al., 2009). Specifically, price elasticities of demand for residential and retail uses have been examined at national, regional, and state levels (Alberini, et al., 2011; Bernstein and Griffin, 2005; Fell et al., 2010; Paul et al., 2009). For example, Fell et al. (2010) found that price-elasticity estimates vary across the four census regions of the United States. They found that the South (–1.02) and North (–0.82) were the most and least price-elastic regions with little variation across income quartiles within each region.

Despite the abundance of literature dealing with regional and usage variations in price elasticities of electricity demand, adequate attention has not been given to evaluating regionally varying electricity-pricing systems and the spatial-dynamic processes in electricity consumption. The lack of research evaluating regionally varying pricing systems is surprising, given that regionally varying pricing systems have been adopted in the United States, the United Kingdom, and Japan, among others, and are being considered in countries like South Korea to regulate the excess demand for electricity (Korean Ministry of Strategy and Finance, 2012; The Federation of

Electric Power Companies of Japan, 2012; Torse, 2013; UK Power, 2014; US EIA, 2014a, 2014b).

Likewise, the lack of research dealing with the spatial-dynamic processes in electricity consumption is unexpected, because electricity consumptions in one region is likely influenced by electricity consumption in neighboring regions that are interrelated socially and economically (Blázquez et al., 2013). Our research fills these two gaps in knowledge by using a spatial-panel model that incorporates spatial spillover effects to simulate spatial variations in electricity demand by comparing regionally-varying and regionally-uniform pricing systems.

1.2. Objectives and significance

The objective of our research is to predict how electricity demand varies spatially between *status quo* regionally-uniform electricity pricing and regionally-varying electricity pricing according to the source of demand (use). Using our spatial-panel model, we test three hypotheses: (1) price elasticities of electricity demand differ across uses, (2) spatial spillover effects exist for different uses, and (3) changes in electricity demand vary across regions and uses between *status quo* regionally-uniform electricity pricing and regionally-varying electricity pricing systems.

We used electricity demands for manufacturing, agricultural, residential, and retail uses between 2004 and 2012 in 16 regions of South Korea as a case study.[1] Econometric estimates from the spatial-panel model were used to simulate changes in future electricity demand under the current government plan of increasing electricity prices with variation across uses but

[1] Using a longer period of data would have been better for the analysis; however, consistent data were not available prior to 2004.

without regional variation and under a hypothetical scenario that increases electricity prices differently across regions as well as uses, given regional electricity self-sufficiency constraints (see details in *Hypothetical electricity pricing scenarios*).

Our research contributes to the literature in two ways. First, our spatial-panel model accommodates spatial spillovers and spatial clusters of electricity consumption. Among the many studies that estimate the price elasticity of electricity demand using aggregate regional panel data (e.g., Alberini and Filippini, 2011; Bernstein and Griffin, 2005; Blázquez et al., 2013; Houthakker, 1980; Hsing, 1994; Maddala et al., 1997; Paul et al., 2009), few have examined location-specific price elasticity estimates based on regional panel data (e.g., Bernstein and Griffin, 2005; Blázquez et al., 2013). The importance of incorporating spatial-dynamic processes in the electricity demand model was discussed by Blázquez et al. (2013). Although they explicitly modeled electricity demand assuming a spatial-dynamic structure, the structure was specified without systematic testing. Spatial econometrics literature emphasizes the need to identify the type of spatial-dynamic process for each dataset based on systematic testing (Anselin, 1988; Anselin et al., 1996; Burridge, 1980; Elhorst, 2010). Accordingly, we applied the general-to-specific approach for specifying the potential spatial-dynamic structure.

Second, the empirical findings of our spatial-panel model facilitate decomposing the price elasticity of demand into the direct elasticity (i.e., the effect of a change in the electricity price in the *i*th region on electricity demand in the *i*th region plus the effect neighboring regions' demand exerting a feedback influence on the *i*th region's electricity demand) and the indirect elasticity (i.e., the sum of the effects of a change in the *i*th region's electricity price on the electricity demands in the other regions). The direct and indirect elasticities are summed and defined as the total elasticity. By doing so, we were able to perform *ex-ante* simulations to predict and compare the spatial heterogeneities in the electricity demands between *status quo* regionally-uniform electricity pricing and hypothetical regionally-varying electricity pricing across uses.

Our comparison of *ex-ante* predictions provides useful information for decision makers interested in restructuring the electricity pricing system from a regionally-uniform to a regionally-varying pricing system. The *ex-ante* simulations provide a useful tool for examining the potential impacts of implementing a regionally-varying electricity pricing system before changes in the pricing system are actually implemented, helping to identify and avoid any potential down-side risks of implementation.

In the following section, we present the conceptual framework for the electricity demand equations based on the input-cost minimization problem for a production input for manufacturing, agricultural, and retail uses and the electricity demand function from the utility maximization problem for residential use. Empirical models are specified following the conceptual framework. A description of the study area and data, empirical results, and conclusions follow.

2. Methods

2.1. Conceptual framework

The electricity demands for manufacturing, agricultural, and retail uses are derived from the input-cost minimization problem because electricity is an input used in producing the outputs of these sectors. The production function for output Q is:

$$Q = f(K, L, S) \tag{1}$$

where K is capital, L is labor, S is source of energy including electricity, petroleum, coal, and natural gas. Based on the duality between the cost and production functions (Hackman, 2008), the solution to the input-cost minimization problem yields a cost function C:

$$C(r, w, s, Q), \tag{2}$$

where $r, w,$ and s are, respectively, prices of K, L, and S. Assuming homothetic separability (Chambers, 1997; Hackman, 2008; Lewbel, 2003),[2] the separability of S from (K, L) in the production function is equivalent to the separability of s from (r, w) and Q in the cost function. The homothetic separability assumption gives a cost function for electricity C_E that is independent from the level of output Q and the prices of non-energy inputs (i.e., r, w):

$$C_E(P_E, P_P, P_C, P_N), \tag{3}$$

where P_E, P_P, P_C, P_N are, respectively, prices of electricity, petroleum, coal, and natural gas. Applying Shephard's lemma (Hackman, 2008) to the above cost function, the conditional factor demand function for electricity E is:

$$E(P_E, P_P, P_C, P_N, Q), \tag{4}$$

Assuming electricity is a good demanded by households, electricity demand for residential use is determined from households' desires to maximize utility given their income constraints. The solution to the utility maximization problem yields the electricity demand function for residential use, which is a function of the prices of electricity, other substitute energy sources and other goods, and household income Y:

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[2] Homothetic separability is commonly assumed in modeling firm production and estimating production or cost functions (Lewbel, 2003). Suppose we have a homothetic function $r(x_0, x_1, ..., x_k) = h[g_1(x_1), ..., g_k(x_k), x_0]$ for vectors $x_0, x_1, ..., x_K$, where h is strictly monotonic and g is linearly homogeneous, homothetic separability implies that each g_k function can be estimated separately.

$$E(P_E, P_P, P_C, P_N, Y)\,. \tag{5}$$

Here, energy prices and income are expressed in real terms—deflated by a price index representing the prices of other goods as the numeraire—because conditional input demand functions are homogeneous of degree zero in prices of goods and income (or output) (Fuss and McFadden, 1978; Nicholson and Snyder, 2012).

2.2. Empirical model

Following the conceptual framework expressed in equations (4) and (5), we specify the electricity demand equations for the four uses as[3]:

$$\ln E_{it} = \ln P_{it}\gamma + \ln X_{it}\beta + u_i + \delta_t + \varepsilon_{it}\,, \tag{6}$$

where subscripts i and t represent region i (i = 1, 2, ... , 16) and year t (t = 2004, 2005, …, 2012), repectively; E_{it} is electricity demand in gigawatt hours (GWh); P_{it} is a vector of prices of electricity in Korean won (KRW) per kilowatt hour (KRW/KWh), petroleum (KRW/liter), coal (KRW/ton), and natural gas (KRW/m^3); X_{it} is a vector of other electricity demand factors (i.e., value-added, work force, population, and weather and climate); γ and β are vectors of the parameters to be estimated; u_i captures region-specific, year-invariant effects; δ_t captures time-specific, region-invariant effects; and ε_{it} is an independently and identically distibuted error terms, $\varepsilon_{it} \sim (0,\ \sigma^2_\varepsilon)$.

The quantities of output Q in equation (4) for manufacturing, agricultural, and retail uses are represented by the respective values-added for the three sectors, and the sum of the values-

[3] For simplicity, notation for the four uses is suppressed as the same model is applied for each use.

added for those sectors represents aggregate household income *Y* in equation (5). The work forces employed in the manufacturing, agricultural, and retail sectors control for the scale of electricity demand in those sectors, total population controls for the scale of residential electricity demand (Darmstadter, 2004; Neelsen and Peters, 2011; Stern, 1993). Annual heating days, annual cooling days, and average temperature control for the effects of weather and climate-related factors in the four electricity demand equations (Krese et al., 2011; US EIA, 2009).

We performed three tests (i.e., test for fixed or random effects, test for serial correlation, and test for spatial autocorrelation) for each of the four equations represented by equation (6) to determine the most appropriate estimation framework. F-statistics for the test of spatial fixed effects across the 16 regions ranged from 14.6 to 2,169.1 for the four uses, which indicated the presence of spatial heteroscedasticities (p-value = 0.000), while F-statistics for the test of time fixed effect across the nine years ranged from 0.06 to 0.71 for the four uses, which indicated no temporal heteroscedasticities. Breusch and Pagan Lagrangian multiplier tests (Baltagi et al., 2008; Breusch and Pagan, 1979) found significant random effects for retail electricity demand (χ^2 = 479.56, p-value = 0.000), however, the Hausman test (Baltagi et al., 2008; Greene, 2008) rejected the null hypothesis that the random-effects model is preferred over fixed effects model for retail use (χ^2 = 34.93, p-value = 0.000). Therefore the spatial fixed effect models were chosen for all four uses.

Serial correlation across the nine years may result in inefficient parameter estimates when estimating the panel data model specified in equation (6). Wooldridge tests (Drukker, 2003; Wooldridge, 2002) for serial correlation produced F-statistics of 202.3, 339.0, 432.0, and 44.5, respectively, for manufacturing, agricultural, retail, and residential uses, which indicate rejection of the null hypothesis of no serial correlation. Thus, we identified a number of time lags using the Augmented Dickey Fuller (ADF) test (Im et al., 2003). According to the ADF test results, we used a first-order autoregressive (AR(1)) panel framework for all four uses.

We hypothesized the spatial lag of electricity demand and spatially correlated errors of the equation based on different row-standardized spatial weight matrices (i.e., K-nearest neighbor (KNN, K= 3, 4, and 5), Thiessen polygon, inverse distance, and hybrids between inverse distance and KNN or Thiessen polygon matrices).[4] The robust spatial Lagrange multiplier (LM)-lag statistics of 0.65 – 18.574 suggest that at least 4 of 9 weight matrices for each sector rejected the aspatial model over the spatial lag model, and the robust spatial LM-error statistics of 0.042 – 52.021 suggested that at least 5 of 9 weight matrices for each sector rejected the aspatial model over the spatial error model (critical value = 3.84). Based on these results, we re-specified equation (6) using the Spatial Autocorrelation (SAC) Model (Elhorst, 2010; LeSage and Pace, 2009) to accommodate both spatial lag and spatial error processes in the AR(1) panel framework (referred to as SAC-AR(1) model):

$$\begin{aligned} \ln E_{it} &= \delta \ln E_{i,t-1} + \rho \sum_{j=1}^{n} w_{ij} \ln E_{it} + \gamma \ln P_{it} + \ln X_{it}\beta + u_i + e_{it} \\ e_{it} &= \lambda \sum_{j=1}^{n} w_{ij} e_{it} + \varphi_{it} \end{aligned} \tag{7}$$

where w_{ij} is element (i, j) of the spatial weight matrix $\mathbf{W}$, ρ is the parameter of spatially lagged electricity demand, and φ_{it} is the independently and identically distibuted error terms for i and t,

[4] The KNN matrix identifies the number (k) of nearest regions as neighbors based on Euclidian distance between the centroids of regions. The Thiessen polygon weight matrix calculates the regions surrounding a region in a method that recognizes the adjacent neighbors (Anselin 1988). The inverse distance matrix captures continuous distance-decay effects among regions at different distances. The hybrid matrix was created by joining inverse distance and either a Thiessen polygon weight matrix or a KNN weight matrix. This approach computes the Euclidian distances between the centroids of regions before taking the inverse values and using them as the off-diagonal elements of the spatial weight matrix. The KNN and Thiessen polygon weight matrices only account for discrete classification of neighbors, whereas the hybrid matrix accounts for both continuous distance-decay effects and the effects of discrete classification of neighbors.

$\varphi_{it} \sim (0,\ \sigma_e^2)$. The lagged dependent variable in equation (7) is assumed to be predetermined in the AR(1) panel framework (Arellano and Honoré, 2001) and uncorrelated with the error term.

We estimated equation (7) for manufacturing, agricultural, retail, and residential uses with the Stata module for spatial panel data created by Belotti et al. (2013) using maximum likelihood based on the following log-likelihood function for n = 16 regions and T = 9 years (Lee and Yu, 2010):

$$\ln L_{\mathrm{n,T}} = -\frac{nT}{2}\ln(2\pi\sigma^2) + T\left[\ln|\mathbf{I}_n - \rho\mathbf{W}|\right] + \ln|\mathbf{I}_n - \lambda W| - \frac{1}{2\sigma^2}\sum_{t=1}^{T} V_{nt}^{'} V_{nt}, \tag{8}$$

where $V_{nt} = (\mathbf{I}_n - \lambda\mathbf{W})\big((\mathbf{I}_n - \rho\mathbf{W})y - Z\eta\big)$ in which Z denotes vectors of independent variables and η is a vector of corresponding parameter estimates.

Once the parameters of the four models were estimated, we estimated direct, indirect, and total price elasticities using the spatial dependence structure (LeSage and Pace, 2009). The total elasticity of the kth variable was estimated as:

$$n^{-1}\iota_n'\left[(\mathbf{I}_n - \rho\mathbf{W})^{-1}\mathbf{I}_n\gamma_k\right]\iota_n = n^{-1}\left[\sum_{i=1}^{n}\sum_{j=1}^{n} v_{i,j}\gamma_k\right], \tag{9}$$

where γ_k is the coefficient of the kth variable and $v_{i,j}$ is the (i, j) element of $(\mathbf{I}_n - \rho\mathbf{W})^{-1}$. The total elasticity is equal to the sum of all elements in $[\cdot]$ on the left side of equation (9) divided by n. The direct elasticity was estimated as:

$$n^{-1}tr\left[(\mathbf{I}_n - \rho\mathbf{W})^{-1}\mathbf{I}_n\gamma_k\right] = n^{-1}\left[\sum_{i=1}^{n} v_{i,i}\gamma_k\right]. \tag{10}$$

The direct elasticity is equal to the sum of the diagonal elements of $[\cdot]$ on the left side of equation (10) divided by *n*. The indirect elasticity is the total elasticity minus the direct elasticity and is equal to the sum of the off-diagonal elements of $[\cdot]$ on the left side of equation (10) divided by *n*.

2.3. Forecasting electricity demand

We forecasted electricity demands for the 2013 – 2020 period for each of the 16 regions using the direct, indirect, and total elasticities obtained from the SAC-AR(1) model. We assumed the electricity-price increases in the current government plan and in a hypothetical scenario, *ceteris paribus*. The electricity demands for the four uses were forecasted using the following equation:

$$\ln E_{it} = \left(1-\rho w_{ij}\right)^{-1} \delta \ln E_{i,t-1} + \left(1-\rho w_{ij}\right)^{-1} \gamma \ln P_{it} + \left(1-\rho w_{ij}\right)^{-1} \ln X_{it}\beta \,. \tag{11}$$

The current government plan to increase electricity prices based on expected inflation was finalized in February 2013 as a part of the 6th Electricity Supply and Demand Plan by the Ministry of Trade, Industry, and Energy of South Korea (Hoe, 2013; Jeon, 2013). While the plan is still under public criticism and also has potential to be revised, we applied the current government plan as our baseline scenario for the *ex-ante* simulations. Specifically, for the baseline scenario with regionally-uniform electricity pricing, we assumed nominal electricity prices increase by 5.9%, 5.9%, 7.1%, and 21.4% between 2013 and 2020 for manufacturing, agricultural, retail, and residential uses, respectively. For consistency with elasticity estimates from the model based on the conceptual framework, we deflated the planned electricity prices by the projected consumer price index (Hoe, 2013) to obtain real prices before performing the simulations. The real electricity prices in the baseline scenario decrease by 9.6%, 9.6%, and 8.5% for manufacturing, agricultural, and retail uses and increase by 3.7% for residential use during the 2013 – 2020 period (see Table 2 for the planned annual changes of in nominal and real prices).

The hypothetical scenario was simulated based on suggestions from electricity market experts in South Korea, who have emphasized the need for regionally-varying electricity prices that incorporate the varying costs of electricity supply (Korean Ministry of Strategy and Finance 2012). The experts suggested that electricity prices should be lower in regions with self-sufficiency in electricity supply than in regions without self-sufficiency (HRI, 2013). Their argument is that the cost of supplying electricity to the regions without self-sufficiency is greater than the cost of supplying the self-sufficient regions because of the extra cost to construct transmission facilities to transmit electricity to the regions without self-sufficiency.

Following the experts' suggestions, we developed a hypothetical scenario by revising the current government plan to reflect regionally-varying electricity pricing based on electricity supply self-sufficiency (HRI, 2013). In the hypothetical scenario, six self-sufficient regions (i.e., Busan, Chungnam, Gyungbuk, Gyungnam, Incheon, and Jeonnam) received a lower electricity price than the baseline scenario and 10 regions lacking self-sufficiency (i.e., Chungbuk, Daegu, Daejeon, Gangwon, Gwangju, Gyeonggi, Jeju, Jeonbuk, Seoul, and Ulsan) received a higher electricity price than the baseline scenario. Specifically, we assumed hypothetical nominal electricity price increases of (*i*) 50% less than the baseline scenario for the 6 regions with self-sufficient electricity supply and (*ii*) 50% more than the baseline scenario for the 10 regions without self-sufficient electricity supply. We calculated the price increases for the hypothetical scenario with regionally-varying electricity pricing for all four uses as:

$$
\begin{aligned}
P^{ss}_{2012+\tau} &= P_{2012} + (P^{c}_{2012+\tau} - P_{2012}) \times 0.5 \\
P^{ns}_{2012+\tau} &= P_{2012} + (P^{c}_{2012+\tau} - P_{2012}) \times 1.5
\end{aligned} \tag{12}
$$

where $P^{ss}_{2012+\tau}$ is the hypothetical price for the 6 regions with self-sufficient electricity supply in 2012+τ, $P^{ns}_{2012+\tau}$ is the hypothetical price for the 10 regions without self-sufficient electricity supply in 2012+τ, P_{2012} is the actual electricity price in 2012, $P^{c}_{2012+\tau}$ is the baseline price of the current government plan in 2012+τ, and $\tau = 1,2,\ldots,8$.

Once we calculated the hypothetical nominal price increases, we deflated the price increases by the projected consumer price index (Hoe, 2013) before performing the simulations. Real electricity prices were projected to increase by 12.0%, 12.0%, 11.5%, and 4.8% over the 2013 – 2020 period for manufacturing, agricultural, retail, and residential uses for the 6 regions with self-sufficient electricity supply. Alternatively, real electricity prices were projected to decrease by 7.2%, 7.2%, and 5.7% for manufacturing, agricultural, and retail uses and to increase by 12.4% for residential use for the 10 regions without self-sufficient electricity supply.

We conducted sensitivity analysis using the hypothetical scenario with regionally-varying nominal electricity price increases of 25% and 75% less than the baseline scenario for self-sufficient regions, and increases of 25% and 75% more than the baseline scenario for the regions lacking self-sufficiency. We graphed the electricity demand forecasts from 2013 to 2020 for the current government plan and for the hypothetical scenario with 50% lower nominal increases for self-sufficient regions and 50% higher nominal increases for the other regions (referred to as "the 50% scenario"). We also mapped the predicted spatial variation of the changes in electricity demands between the baseline and the 50% scenario.

2.4. Data

The electricity demands and prices across the entire region for 2004 – 2012 were obtained from the *Yearbook of Energy Statistics*, published by the Korean Energy Economics Institute (KEEI, 2013). The anticipated electricity prices under the current government plan were obtained from the Ministry of Trade, Industry, and Energy of South Korea (Hoe, 2013; Jeon, 2013). Gasoline prices, natural gas prices, and fossil fuel prices for 2004 – 2012 were obtained from the Korea Energy Statistics Information System (KESIS, 2013). The work forces, total populations, and the values added at the regional level for 2004 – 2012 were collected from the Korean Statistical Information Service (KOSIS, 2013). The electricity prices, gasoline prices, natural gas prices, fossil fuel prices, and the values added were deflated by consumer price index (KOSIS, 2013).

The average annual high and low temperatures, which were used to indicate the number of days for energy needed to heat (i.e., the temperature is less than or equal to 18 degrees Celsius) and cool (i.e., the temperature is greater than or equal to 26 degree Celsius) buildings, respectively, were collected at the regional level for 2004 – 2012 from the *Monthly Energy Statistics* published by the Korea Energy Economics Institute (KEEI, 2013). Annual average temperatures were collected from the *Annual Climatological Report* published by the Korea Meteorological Administration (KMA, 2013). Meteorological measurements of temperature were observed from 78 stations throughout the country. We assigned the average temperatures of synoptic stations that fell within the boundaries of each region for 2004 – 2012. The boundary data of the 16 regions were collected in shape files from BIZ-GIS.com (BIZ-GIS, 2013).

3. Results and Discussion

3.1. Estimation results and discussion

We estimated the SAC-AR(1) models for manufacturing, agricultural, retail, and residential electricity demand using the K-nearest neighbor (K=5), K-nearest neighbor (K=5), inverse distance, and inverse distance weight matrices, respectively, based on best goodness of fit. The selection of a spatial weight matrix had minor influence on the overall fit (i.e., AIC values of -443.0 ~ -413.3, -397.0 ~ -394.8, -318.7 ~ -316.3, -545.0 ~ -534.8, respectively, for manufacturing, agricultural, retail, and residential electricity demand).

The spatial strucutre for manufacturing reflected in the K-nearest neighbor weight matrix can be explained by clustering in the manufactring sector of South Korea. As examples, the manufacturing sector has two industrial clusters—Seoul and its neighboring regions and the Gyeongsang regions (Choi and Kim, 2010). The two clusters are not contiguous and thus the selected K-nearest neighbors spatial weight matrix fits the spatial relationships in the two clusters' electricity demands. On the other hand, the spatial demand relationship in the residential sector is well characterized by the inverse distance matrix that captures continuous distance-decay effects. The continuous distance-decay effects portray the global spatial dependence in residential electricity demands across the country as a whole.

Table 3 presents the parameter estimates and their standard errors from the SAC-AR(1) models for the four electricity demand equations. The spatial lag of electricity demand (ρ) is positive for manufacturing and residential uses, negative for agriculture use, and not significant for retail use. These findings suggest (*i*) positive spatial spillovers in electricity demand for manufacturing and residential uses, (*ii*) negative spatial spillovers in electricity demand for agricultural use, and (*iii*) no spatial spillovers in retail use.

The spatial spillovers capture spatial linkages associated with electricity demands other than those captured by the explanatory variables in the regressions. For example, the positive spillovers in manufacturing might be explained by the electricity demand in a region with automobile assembly facilities affecting the electricity demands in neighboring regions where automobile parts are produced and supplied to the assembly facilities. The positive spillovers in residential use capture the dependence of residents' socio-economic activities among neighboring regions, including life-style trends and consumer behaviors that result in similar patterns of residential electricity demand within neighboring regions (Jeeninga and Huenges Wajer, 2007).

In contrast, the negative spillovers in agricultural use suggest that an increase in agricultural electricity demand in one region is associated with lower agricultural electricity demand in neighboring regions. This finding implies that neighboring regions are more dissimilar in agricultural electricity demand than if regions were distributed randomly (Kao and Bera, 2013). The lack of spatial spillovers in retail use suggests that electricity demands vary randomly across regions. The significant spatial error coefficients (λ) suggest that a random shock in a spatially significant omitted variable that affects electricity demand for agricultural (or retail use) in a region triggers a positive change in the electricity demand in that region and a positive (negative) change in agricultural demand (retail demand) in neighboring regions.

The direct, indirect, and total elasticities of the explanatory variables are presented in Table 4. A 1% increase in time-lagged electricity demand in a region increased current-period electricity demand by (*i*) 0.57%, 1.00%, and 0.56% in the same region, (*ii*) 0.24%, -0.21%, and 0.10% in neighboring regions, and (*iii*) 0.81%, 0.80%, and 0.66% in South Korea as a whole, respectively, for manufacturing, agricultural, and retail uses. Although the total elasticities of time-lagged electricity were quite similar across the uses, the indirect elasticities varied substantially (between 0.24 for manufacturing use and -0.21 for agriculture use). The positive indirect elasticity of time-lagged electricity demand for manufacturing use is associated with the positive spatial spillover in manufacturing use. Likewise, the negative indirect elasticity of time-lagged electricity demand for agriculture use is associated with negative spatial spillovers in agriculture use.

The total price elasticities of electricity demand were -1.10 and -1.21, respectively, for manufacturing and retail uses while their counterparts for agriculture and residential uses were not significant. These findings suggest that demands for manufacturing and retail uses were price elastic, while they were not significantly different from zero for agricultural and residential uses. These price elasticity estimates are within the range of those reported in the literature (see Table 1).

The cross-price elasticities of demand with respect to prices of petroleum, coal, and natural gas show various results. The total cross-price elasticities suggest that a 1% increase in the petroleum price decreases electricity demand for manufacturing and retail uses by 0.16% and 0.19%, respectively, suggesting that petroleum and electricity are complement inputs in the manufacturing and retail sectors. Similarly, the total cross-price elasticity for coal indicates that a 1% increase in the coal price decreases electricity demand for retail use by 0.24%, reflecting complementarity between coal and electricity in the retail sector. In contrast, the total cross-price elasticity of demand with respect to the natural gas price (0.16%) indicates substitutability between natural gas and electricity in the retail sector.

The work-force elasticities of electricity demand are positive for manufacturing use. Specifically, a 1% increase of the work force in a region increased electricity demand for manufacturing use in that region, in neighboring regions, and in the entire country by 0.31%, 0.13%, and 0.44%, respectively.

A 1% increase in value-added increased South Korean electricity demands for manufacturing and retail uses by 0.31% and 0.86%, respectively. Spatial spillover effect for manufacturing was 0.09%, but no significant for retail use. These findings suggest that increases in electricity use in the manufacturing sector increase the level of manufacturing output (i.e. value-added) through spatial spillovers, confirming previous findings in the literature (Lam and Shiu, 2004; Narayan et al., 2008; Mellicianі and Peracchi, 2006).

The significant total elasticities for average temperature and average cooling and heating days have the expected signs. A 1% increase in average temperature or cooling days increased electricity demand for agricultural use by 0.66% and 26%, respectively, and a 1% increase in heating days increased electricity demand for retail use by 0.74%. These positive total elasticities for the agricultural sector likely imply greater electricity demand by greenhouse operations in warmer regions of the country, while the positive total elasticity for heating days suggests greater demand for electricity by retail outlets in cooler regions of the country. The insignificant average temperature for the manufacturing, retail, and residential sectors are consistent with the insignificant time fixed effects reported earlier.

3.2. Simulation results and discussion

Fig. 1 shows that electricity uses between 2013 and 2020 in the manufacturing, agricultural, and retail sectors were forecast to increase by 19.8%, 38.4%, and 27.4%, respectively, for the baseline scenario, and 19.3%, 37.1%, and 23.2%, respectively, for the 50% scenario, while residential use was forecast to decrease by 0.7% for the baseline and 1.1% for the

50% scenario. These predicted changes were closely associated with the decreases in real electricity prices for manufacturing, agricultural and retail uses and the increase in the real electricity price for residential use between 2013 and 2020.

The electricity demands of the hypothetical scenario were lower than those of the baseline throughout the period of 2013 – 2020 across all four uses. The gap for retail use widened by 6.77 terawatts (from 0.87 to 7.64 terawatts) from 2013 to 2020, while corresponding gaps for manufacturing, agricultural, and residential uses widened by much smaller amounts of 1.29, 0.20, and 0.25 terawatts, respectively. The gap is wider in 2020 for retail use mainly because regions without self-sufficiency in electricity consumed 33% more electricity for retail use than self-sufficient regions, and the total price elasticity for retail use has a relatively larger negative effect (less than -1) than the price elasticities for the other uses (greater than -1). The sensitivity tests performed by the 25% and 75% scenarios show that the widening gap in electricity demand for retail use relative to other uses is not sensitive to the degree of regionally-varying electricity pricing.

Fig. 2 visually highlights spatial variations between differences in the 50% scenario and the baseline scenario by showing regional differences in the percentage changes in electricity demand. The maps shows that the 10 regions without self-sufficient in electricity supply would have lower electricity demands under the 50% scenario than under the baseline scenario by 4.8% to 7.3%, 2.2% to 18.5%, 8.6% to 10.0%, and 0.7% to 1.2% for manufacturing, agricultural, retail, and residential uses, respectively. Conversely, the maps show that the 6 regions with self-sufficient electricity supply would have higher electricity demands under the 50% scenario than under the baseline scenario by 4.0% to 6.4%, 9.9% to 16.4%, 8.2% to 8.8%, and 0.5% to 0.8% for manufacturing, agricultural, retail, and residential uses, respectively. Thus, spatial variation in differences between electricity demands was highest for agricultural use and lowest for residential use.

The information in Fig. 2 also suggests that electricity use in all sectors would be decentralized if regionally-varying electricity pricing were adopted. For example, the share of agricultural electricity use in the Gyeonggi region (highest use region) would decline from 23.5% to 19.4% in 2020, while the share in the Chungnam region would increase from 11.4% to 13.1% (see Table 5). Consequently, electricity demand in the 6 regions with self-sufficiency would increase by 27% (from 195 terawatts to 247 terawatts) and in the 10 regions without self-sufficiency it would increase by 11% (from 274 terawatts to 305 terawatts) by 2020 (see Table 6). In contrast, electricity demand was predicted to increase by about the same amount (i.e., 19.7% and 20%) by 2020 in the two regions under the government plan (baseline scenario) of regionally-uniform pricing.

4. Conclusions and Policy Implications

We summarize our empirical results of the South Korean case study with three key findings and implications that can be generalized to other countries where spatial-dynamic processes in electricity demand exist and regionally-varying pricing policies are being considered. First, we found that price elasticities of electricity demand differ according to use. Specifically, electricity demands for agricultural and residential uses were close to perfectly inelastic and those for manufacturing and retail uses were inelastic and close to unit elastic, respectively. This information is important to policy makers in designing electricity-price policy. Our results suggest that particular care should be exercised in determining future price increases for manufacturing and retail uses, because the potential for slower growth in electricity demand could slow the rates of development of those sectors.

Second, our findings confirm that spatial spillovers in electricity demands vary across different uses. Specifically, positive spatial spillovers were found in the manufacturing and residential sectors, negative spatial spillover was found in the agricultural sector, and no spatial spillovers were found in the retail sector. Understanding the spatial structures of electricity demand in these sectors will help policy makers anticipate the spatially-varying impacts of electricity-pricing policy across regions. The positive spatial spillovers in manufacturing and residential uses will be particularly useful in designing an energy policy that includes regionally-varying electricity pricing. For example, increasing the electricity price for manufacturing use in clusters of manufacturing regions (e.g., Ulsan, where major automobile manufacturers are located) would not only decrease manufacturing electricity demand in those regional cluster, but also in neighboring regions (e.g., Gyeongbuk). Likewise, increasing the residential electricity price in a region would result in a decrease in residential electricity demand in that region and in neighboring regions. For example, an increase in the residential electricity price in Seoul would decrease the electricity demand for residential use in Seoul and in its neighboring region, Gyeonggi. As a result, residential use in the Seoul and Gyeonggi regions, which include 46% of South Korea's total residential use, would be affected by the price increase instead of residential use in Seoul alone, which constitutes only 23% of residential electricity use.

Third, our simulations show that spatial variations between electricity demands with regionally-varying electricity pricing and those with regionally-uniform electricity pricing vary by use. For example, our results suggest that differences in spatial variation between the two pricing policies would be highest for agricultural use and lowest for residential use. The higher regional variation between the two pricing policies for agricultural use implies more regional sensitivity in electricity demand with the regionally-varying pricing policy. This finding suggests more care by policy makers in determining future electricity price increases in that sector than for residential use. In addition, our predicted differences in the spatially-varying impacts on electricity demands between the two policies will help policy makers in considering establish more realistic regionally-varying electricity pricing according to use.

Although our study provides a useful comparative analysis of anticipated changes between regionally-uniform and regionally-varying pricing policies according to use, we do not provide information about the economic consequences of implementing regionally-varying electricity-pricing policy. A complementary analysis identifying the potential economic impacts would help South Korean policy makers anticipate the regional and national economic consequences of a regionally-varying electricity pricing policy. Future analyses linking impacts on electricity demand and economy activity would be beneficial in generating more complete information for restructuring electricity-pricing policy.

Although we deal with the spatial-dynamic processes in the dependent variable (electricity demand), the explanatory variables are treated as spatially invariant. This assumption is consistent with our electricity demand equations because the explanatory variables are spatially invariant (i.e., electricity price, petroleum price, coal price, and natural gas price) in South Korea. A larger study area (e.g., the United States) would require specification of spatial-dynamic processes in both dependent and explanatory variables (e.g., electricity price), which are more likely spatially variant. For such cases, a spatial Durbin model (Anselin 1988) may be more appropriate.

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Table 1
Price elasticities of manufacturing, agricultural, residential, and retail electricity demand found in previous literature.

Authors	Estimation methods	Manufacturing	Agricultural	Retail	Residential
Alberini et al. (2011)	Dynamic panel	-1.10 ~ -0.08			
Beenstock et al.(1999)	Dynamic, OLS	-0.44 ~ -0.31			
Bernstein & Griffin (2005)	Panel				-0.32 ~ -0.24
Bjørner et al. (2001)	Panel	-0.57			-0.36 ~ -0.13
Bohi & Zimmerman (1984)	Meta analysis	-1.05 ~ -0.00		-0.7	
Bohi (1981)	Dynamic	-1.60 ~ -0.56			
Bose&Shukla (1999)	Panel	-0.45 ~ -0.04	-1.35	-0.26	-0.65
Espey & Espey (2004)	Meta analysis				-2.25 ~ -0.04
Fan & Hyndman (2011)	Time series	-0.428 ~ -0.363			
Fell et al. (2010)	OLS, GMM				-1.02 ~ -0.82
Inglesi-Lotz & Blignaut (2011)	SUR	-0.869	0.152		
Jamasb & Meier (2010)	Panel				0.098
Kamerschen & Polemis (2004)	Time series	-0.55 ~ -0.34			
KEEI (2011)	ARDL	-0.1			
KEEI (2012)	OLS, Time series AR(1)	-1.043 ~ -0.023	-2.389 ~ -2.208		-0.496 ~ -0.354
Kim (1996)	OLS			-0.004	
Lee et al. (2011)	Panel				
Park et al. (1994)	Dynamic			-0.97	-0.27 ~ -0.22
Paul et al. (2009)	Fixed effect OLS				-0.36 ~ -0.13
Polemis (2007)	Time series	-0.85			
Reiss & White (2005)	GMM				-0.35 ~ -0.15
Silk & Joutz (1997)	Co-integration				-0.25
Taylor (1975)	Review paper	-0.22 ~ -1.82		-1.36 ~ -0.17	-1.20 ~ -0.14
Yu (1996)	OLS, CCR, ARDL	-1.59 ~ -1.42		-0.10 ~ 0.00	-0.38
Average		-0.63	-0.60	-0.44	-0.48

Note: AR is autoregressive model, ARDL is autoregressive distributed lag model, CCR is correlated component regression model, GMM is generalized method of moments, OLS is ordinary least square, and SUR is seemingly unrelated regressions.

Table 2
Planned electricity prices for four uses in South Korea between 2013 and 2020 (Korean won per kilowatt hour).

Year	Manufacturing		Agricultural		Retail		Residential	
2013	93.3	(84.2)	44.4	(40.0)	110.9	(100.0)	128.0	(115.5)
2014	94.7	(82.9)	45.0	(39.4)	112.4	(98.4)	133.0	(116.5)
2015	95.6	(81.3)	45.4	(38.6)	113.4	(96.4)	138.3	(117.6)
2016	96.2	(80.2)	45.7	(38.1)	114.5	(95.4)	140.9	(117.4)
2017	96.8	(79.1)	46.0	(37.6)	115.5	(94.4)	144.4	(118.0)
2018	97.5	(78.1)	46.4	(37.2)	116.6	(93.4)	148.0	(118.6)
2019	98.1	(77.0)	46.7	(36.7)	117.7	(92.4)	151.7	(119.1)
2020	98.8	(76.1)	47.0	(36.2)	118.8	(91.5)	155.4	(119.7)

Note: Numbers in parenthesis are prices deflated by the projected consumer price index (Hoe, 2013). Planned prices for different uses are calculated based on annual price-increase rates according to the 6th Electricity Supply and Demand Plan by the Ministry of Trade, Industry, and Energy of South Korea (Jeon, 2013).

Table 3
Parameter estimates and standard errors of the SAC-AR(1) models for electricity demand by use category.

Variables	Manufacturing	Agricultural	Retail	Residential
ln(Electricity demand in the previous year)	0.563*	0.996*	0.555*	-0.031
	(0.056)	(0.054)	(0.092)	(0.090)
ln(Electricity price)	-0.762*	-0.920	-1.032*	-0.086
	(0.185)	(0.512)	(0.148)	(0.203)
ln(Petroleum price)	-0.108*	-0.037	-0.163*	0.016
	(0.041)	(0.171)	(0.028)	(0.039)
ln(Coal price)	0.061	0.027	-0.203*	0.017
	(0.043)	(0.092)	(0.055)	(0.048)
ln(Natural gas price)	0.251*	-0.136	0.125*	0.057
	(0.120)	(0.187)	(0.052)	(0.107)
ln(Work force)†	0.295*	0.032	-0.090	0.637
	(0.057)	(0.022)	(0.052)	(0.437)
ln(Value-added)	0.224*	-0.010	0.745*	0.173
	(0.050)	(0.044)	(0.158)	(0.136)
ln(Annual average temperature)	0.092	0.825*	-0.067	0.613
	(0.223)	(0.336)	(0.166)	(0.386)
ln(Annual cooling days)	-0.089	0.320*	-0.015	0.000
	(0.059)	(0.151)	(0.037)	(0.082)
ln(Annual heating days)	0.292*	0.195	0.623*	0.210
	(0.137)	(0.210)	(0.109)	(0.179)
Spatial lag electricity demand (ρ)	0.308*	-0.247*	0.151	0.527*
	(0.082)	(0.121)	(0.135)	(0.211)
Spatial error (λ)	-0.146	0.384*	-1.124*	-0.862
	(0.247)	(0.162)	(0.292)	(0.570)

† Total population is used for residential use. * Represents significance at the 5% level.

Table 4
Direct, indirect, and total elasticities by use category for the explanatory variables of the SAC-AR(1) models.

Variables	Manufacturing			Agricultural			Retail			Residential		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
ln(Electricity demand in the previous year)	0.57*	0.24*	0.81*	1.00*	-0.21*	0.80*	0.56*	0.10	0.66*	-0.03	-0.01	-0.04
	(0.05)	(0.09)	(0.12)	(0.05)	(0.08)	(0.09)	(0.08)	(0.11)	(0.14)	(0.11)	(0.21)	(0.31)
ln(Electricity price)	-0.77*	-0.33	-1.10*	-0.89	0.20	-0.69	-1.02*	-0.19	-1.21*	-0.08	-0.05	-0.13
	(0.21)	(0.18)	(0.38)	(0.57)	(0.16)	(0.43)	(0.17)	(0.20)	(0.29)	(0.26)	(0.53)	(0.75)
ln(Petroleum price)	-0.11*	-0.05	-0.16*	-0.02	0.01	-0.02	-0.16*	-0.03	-0.19*	0.02	0.01	0.03
	(0.05)	(0.03)	(0.08)	(0.19)	(0.04)	(0.15)	(0.03)	(0.03)	(0.05)	(0.06)	(0.14)	(0.2)
ln(Coal price)	0.06	0.02	0.09	0.03	-0.01	0.02	-0.20*	-0.04	-0.24*	0.02	0.01	0.02
	(0.04)	(0.02)	(0.06)	(0.09)	(0.02)	(0.07)	(0.06)	(0.05)	(0.1)	(0.05)	(0.1)	(0.14)
ln(Natural gas price)	0.26	0.11	0.37	-0.11	0.02	-0.09	0.13*	0.03	0.16*	0.08	0.09	0.18
	(0.13)	(0.08)	(0.20)	(0.20)	(0.04)	(0.16)	(0.05)	(0.03)	(0.08)	(0.13)	(0.19)	(0.3)
ln(Work force)	0.31*	0.13*	0.44*	0.04	-0.01	0.03	-0.08	-0.02	-0.10	0.17	0.14	0.31
	(0.06)	(0.06)	(0.11)	(0.02)	(0.01)	(0.02)	(0.06)	(0.03)	(0.08)	(0.14)	(0.21)	(0.32)
ln(Value-added)	0.22*	0.09*	0.31*	-0.01	0.00	-0.01	0.73*	0.12	0.86*	0.75	0.75	1.5
	(0.05)	(0.04)	(0.07)	(0.05)	(0.01)	(0.04)	(0.17)	(0.12)	(0.19)	(0.91)	(2.14)	(2.98)
Annual average temperature	0.09	0.04	0.14	0.84*	-0.18	0.66*	-0.05	-0.02	-0.07	0.7	0.74	1.44
	(0.22)	(0.10)	(0.32)	(0.33)	(0.10)	(0.26)	(0.16)	(0.04)	(0.19)	(0.49)	(1.23)	(1.61)
ln(Annual cooling days)	-0.09	-0.04	-0.13	0.32*	-0.07	0.26*	-0.02	0.00	-0.02	0	-0.01	-0.01
	(0.06)	(0.03)	(0.09)	(0.16)	(0.05)	(0.13)	(0.04)	(0.01)	(0.05)	(0.09)	(0.14)	(0.22)
ln(Annual heating days)	0.29	0.13	0.42	0.20	-0.05	0.15	0.63*	0.11	0.74*	0.24	0.28	0.52
	(0.04)	(0.33)	(0.07)	(0.05)	(0.05)	(0.19)	(0.23)	(0.13)	(0.01)	(0.21)	(0.48)	(0.64)

* Represents significance at the 5% level.

Table 5
Simulated shares (%) of forecasted electricity consumption by region and use in 2020.

Region	Manufacturing		Agricultural		Retail		Residential		Total	
	Baseline	Hypothetical	Baseline	Hypothetical	Baseline	Hypothetical	Baseline	Hypothetical	Baseline	Hypothetical
Seoul	0.832	0.793	0.079	0.078	20.197	18.937	22.76	22.634	10.078	9.490
Busan	3.029	3.212	0.728	0.856	5.720	6.470	6.937	7.028	4.357	4.705
Daegu	2.450	2.338	0.457	0.395	3.996	3.793	4.751	4.74	3.196	3.057
Incheon	5.064	5.365	0.753	0.872	4.551	5.119	5.41	5.474	4.786	5.147
Gwangju	1.207	1.154	0.479	0.393	2.388	2.270	2.805	2.79	1.779	1.700
Daejeon	1.128	1.051	0.194	0.169	3.105	2.933	2.913	2.892	1.984	1.869
Ulsan	9.797	9.374	0.578	0.487	2.251	2.141	2.165	2.159	6.017	5.806
Gyeonggi	21.203	19.747	23.493	19.412	22.644	21.208	23.846	23.71	22.015	20.628
Gangwon	2.644	2.494	3.350	2.898	4.750	4.474	2.862	2.853	3.426	3.225
Chungbuk	5.717	5.382	4.474	3.831	3.919	3.696	2.928	2.908	4.733	4.472
Chungnam	14.387	15.238	11.371	13.138	4.996	5.627	3.971	4.01	9.836	10.607
Joenbuk	4.843	4.511	7.979	6.767	3.664	3.462	3.492	3.472	4.381	4.109
Joennam	7.511	7.955	16.432	19.285	3.683	4.149	3.401	3.435	5.997	6.503
Gyeongbuk	12.235	13.080	9.919	11.432	6.290	7.098	4.692	4.753	9.239	10.039
Gyeongnam	7.869	8.227	11.901	13.185	6.455	7.308	6.079	6.156	7.295	7.828
Jeju	0.084	0.080	7.813	6.802	1.390	1.315	0.989	0.985	0.880	0.814

Table 6

Forecasted electricity consumption (terawatts) for regions with electricity self-sufficiency and without self-sufficiency in 2020 for the baseline, 50%, 25% and 75% price-increase scenarios.

	Regions	Manufacturing	Agricultural	Retail	Residential	Total	% change between 2012 and 2020
Baseline	Self-sufficient	142.8	8.9	62.1	19.4	233.4	19.7
	No self-sufficient	142.3	8.5	133.7	44.3	328.8	20.0
Hypothetical							
50%	Self-sufficient	150.6	10.1	67.3	19.6	247.7	27.1
	No self-sufficient	133.2	7.1	120.8	43.8	304.9	11.3
25%	Self-sufficient	148.6	10.1	66.2	19.5	244.6	25.5
	No self-sufficient	135.6	7.1	123.8	43.9	310.4	13.3
75%	Self-sufficient	152.7	10.1	68.5	19.6	250.9	28.8
	No self-sufficient	130.7	7.1	118	43.8	299.9	9.3

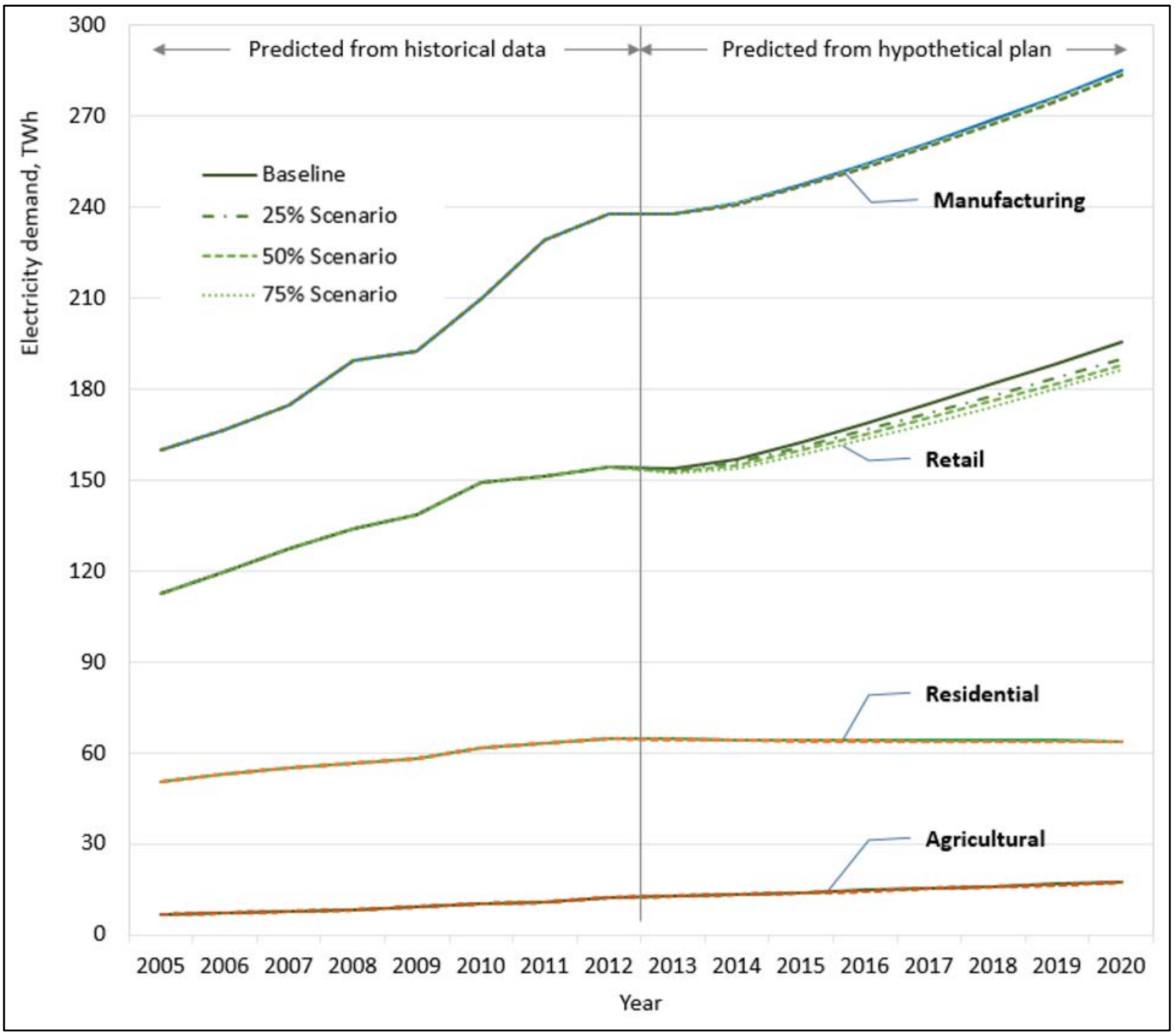

Fig. 1. Simulation results of forecasted electricity demands for four use categories with regionally-uniform electricity pricing (baseline scenario) and with regionally-varying electricity pricing (25%, 50%, and 75% scenarios) during 2013 – 2020.

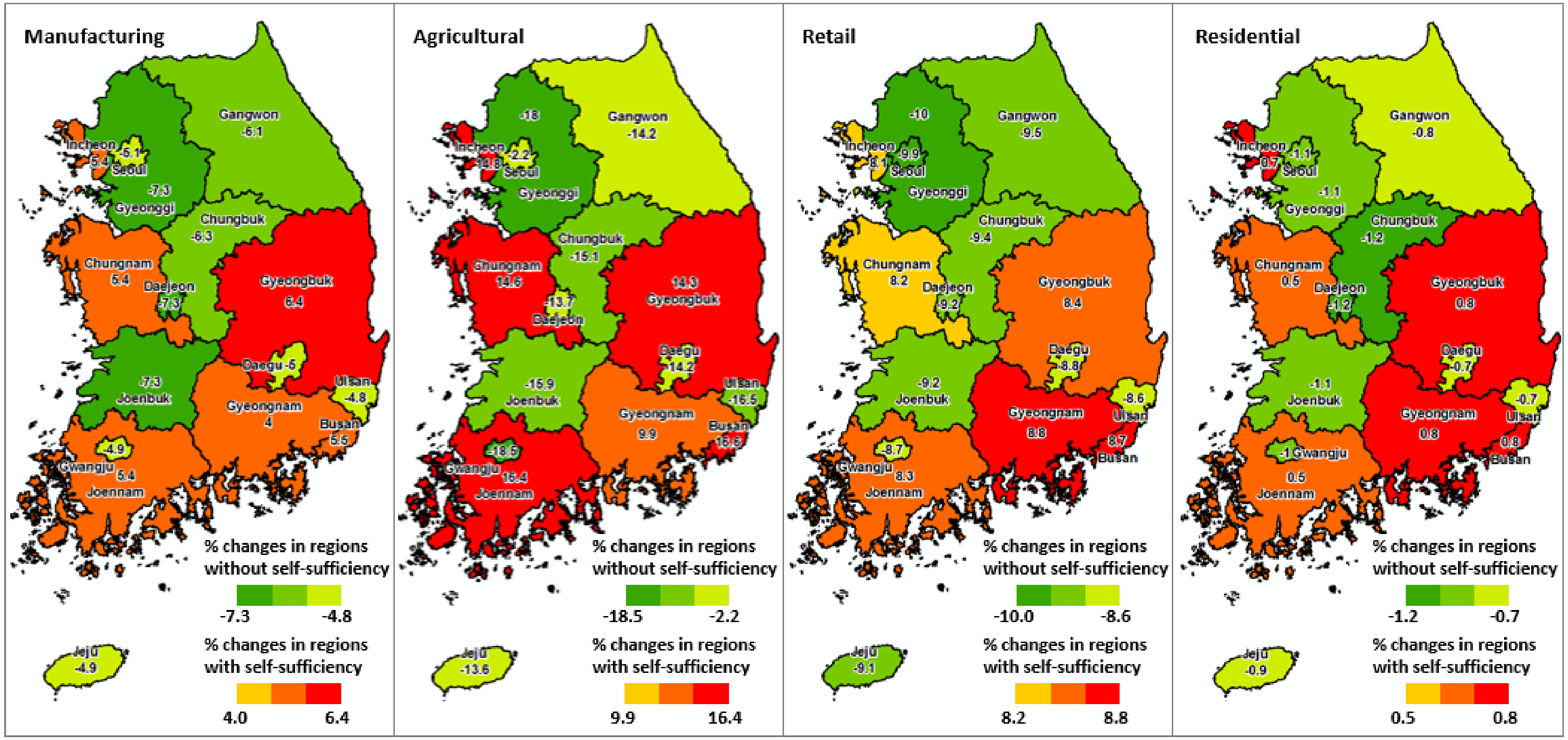

Fig. 2. Spatial variation in percentage differences in electricity demands between the 50% scenario and the baseline scenario in 2020.