Estimating Commercial and Industrial Customer Response to Electricity Critical Peak Prices

Dongsik Jang, Korea Electric Power Corporation (KEPCO), +82-42-865-5112, yojian2@kaist.ac.kr
Jaewoong Lee, College of Business, Korea Advanced Institute of Science and Technology (KAIST), jwlee86@business.kaist.ac.kr
Jiyong Eom, College of Business, KAIST, +82-2-958-3511, eomji@business.kaist.ac.kr

Overview

Demand-side management of electricity is receiving growing attention as a key enabler of the smart grid and a solution for promoting grid resilience to increasing penetration of renewable sources. Despite various demand-side management programs are contemplated and actively implemented by utilities and regulators in North American and European countries, the demand response behaviour of electricity customers to price signal or to incentive payments are not well understood (Neenan and Eom, 2008).

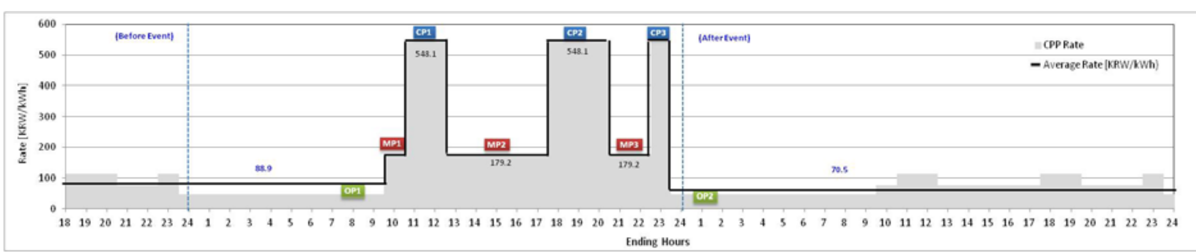
This study investigates the demand response of commercial and industrial customers to the first Korean critical peak pricing (CPP) pilot which was implemented in the winter of 2013. The demand responses of 802 businesses covering 34 commercial and industrial categories are evaluated and characterized based on two different econometric approaches. The first approach utilizes the individual customer baseline loads (CBLs) and a nested constant elasticity of substitution (CES) demand function. The nested CES function is constructed to allow for different levels of price elasticities in different pricing periods, for example, the substitution between the second mid-peak period (13PM-17PM) and the first (11AM-1PM) or the second (18PM-21PM) critical peak period, as well as their respective own-price elasticities (Herriges et al., 1993; Schwarz et al., 2002; Taylor and Schwarz, 1990). Several alternative CPP rate scenarios will be developed to provide policy recommendations.

Second, we estimate own-price and cross elasticities using the demand equation derived from the Generalized McFadden(GM) cost fuction (Diewert and Wales, 1987). Patrick and Wolak (2001) and Taylor et al. (2005) utilized the GM model to estimate elasticities of each pair among separate hours (or semi-hours) in the RTP program. As a second-order flexible functional form, the GM model imposes global concavity in itself. This would resolve the curvature restriction problem in the traditional (first-order flexible) models, such as translog model (Diewert and Wales, 1987). Moreover, the GM model would address the complementarity issue which shows small positive or negative cross elasticities between very adjacent time periods (Patrick and Wolak, 2001). Given that the above nested CES model also concerns this issue, we would compare the reliability of the elasticity estimates derived from the two alternative, qualitatively different demand representations.

Methods

1) Korean CPP pilot program

The Korean CPP pilot program is characterized by a three-tiered rate structure with the default being a time-of-use (TOU) tariff (Figure 1). The rates in peak period—critical and mid-peak periods—under the CPP tariff is set higher than the default TOU tariff: The critical peak price is about 4.8 times higher than the peak price on non-event days with the customers' increased cost burden being offset by decreased costs on the normal days. The CPP consists of eight time blocks in total, comprising three critical peak periods on the event day, three mid-peak periods adjacent to the critical peak periods, and two off-peak periods in both ends of the day. The reason for this unusually complicated tariff design is to maintain a similar structure as the default TOU rate. This multiple, shorter critical peak periods on the event days are expected to make it easier for the customers to shift their electricity loads to neighboring lower priced periods.

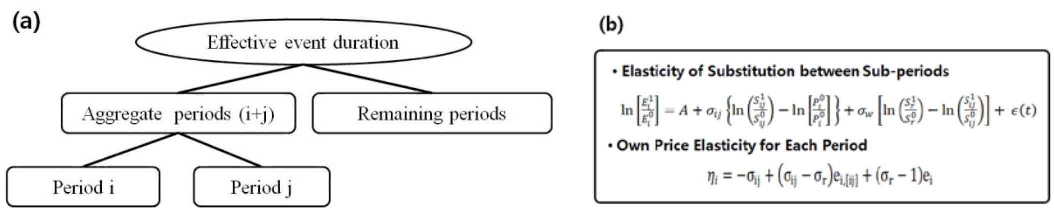


[Figure 1] Rate structure of Korean CPP program for the effective event duration

2) Estimating elasticities using the nested Constant Elasticity of Substitution (CES) model

The process of estimating electricity customers' demand response to the CPP price signal consists of two stages. First, we assess the demand-response load impacts by constructing hourly CBLs for the individual customers and comparing with their hourly load profiles measured on CPP event days. In our study, fixed-effects regression models are used to construct the CBLs, the process of which is documented in Jang et al. (2015). Fixed-effects regression formulation is regarded to give precise and transparent estimates (Woo and Herter, 2006) and has been employed several recent pilot studies as a convenient and reliable way of constructing CBLs (Cappers, et al., 2013; Goldberg and Agnew, 2013). To improve the accuracy of the CBL estimation, we clustered the customers according to the similarity in pre-enrollment hourly load patterns before conducting the fixed-effects regression. Seven fixed-effects regression models are tested for each cluster and the best regression models are selected using goodness-of –fit metrics with the following out-of-sample tests confirming the predictive accuracy of the model (Jang et al., 2015; Bode et al., 2013).

The second stage, which builds on the first, is to represent the customer choice of electricity load within a day and between days, estimating their substitution elasticities. Here we assume that electricity inputs are weakly separable in the production process with the period-level electricity prices and demands fully represented. For example, we treat the three critical peak periods as three separate demand choices within a day, representing their possible substitution with the five other periods within so-called effective event duration. The effective event duration is defined as the 54 hour time window after the notification of the CPP events, indicating the extent to which a customer's behavioural response to a CPP event can take effect. The demand nesting decomposes the effective event duration into eight periods with fixed electricity rates. We estimate the elasticities of substitution within any possible two-period aggregates within the effective event duration at the first level and between the aggregates and the remaining periods at the second level (Figure 2).



[Figure 2] The structure of the customer demand for electricity loads(a) and equations for elasticity estimation(b) using the nested CES model

3) Comparision to the Generalized McFadden (GM) model

As an alternative estimation strategy, we also construct a electicity demand equation based on a Generalized McFadden (GM) cost function. Here we adapt a similar setting proposed by Taylor et al. (2005) for the analysis of Duke Power's real time pricing pilot, accounting for the special features of Korean CPP pilot and its data availability. Our temporal electricity demand function is given as follows:

$$E_{idk} = \left[\frac{1}{PZ_m}\sum_{j=1}^{8} c_{ijk} PE_{jdk} + b_{idk}\right] Y_{dk} + a_{ik} + d_{ik} T_{idk} + U_{idk}$$

E_{idk}: the demand in MW for period i, day d, customer k
PZ_m: the producer price index for month m
PE_{idk}: the price in KRW/MWh for period i, day d, customer k
T_{idk}: the temperature in degrees ℃ for period i, day d, customer k
Y_{dk}: the daily output on day d, for customer k
U_{idk}: the unobserved random vector with mean 0 and covariance matrix Ω

Time period $\mathrm{i} = 1,2,\ldots,8$: 1= period 1(OP1), 8=period 8(OP2)
Day $\mathrm{d} = 1,\ldots,61$: 1=2012 December 3,…, 61=2013 February 28 (only weekdays, 14 weeks)
Customer $\mathrm{k} = 1,\ldots,\mathrm{N}$: (only those belong to sectors with no less than 10 firms)
Month $\mathrm{m} = 1,2,3$: 1=December, 2=January, 3=February

Parameters to be estimated are $a_{ik}, b_{ik}, c_{ijk},$ and d_{ik}. To impose the global concavity in the GM model, we estimate the c_{ijk}'s as $\mathrm{C} = -\mathrm{MM}'$, where M is a lower triangular matrix. This enables the matric C to be negative semidefinite, and the existence of the matrix M is proved by the Lau's theorem (Diewert and Wales, 1987). As we have no information for Y_{dk}, we make the following assumptions for the daily output index (Taylor et al., 2005):

$$Y_{dk} = DOW_{dk} * Week_{dk} * Event_{dk}$$

where each component is of the general form:

$$\text{DOW} = 1 + e_1 * Monday + \cdots + e_4 Thursday$$

$$\text{Week} = 1 + f_1 * Week1 + \cdots + f_{13} Week13$$

$$\text{Event} = 1 + g_1 * PresidentElection$$

Here, we restrict each parameter (e_i, f_i, g_i) to be greater than (-1) so that Y_{dk} to be positive so as to avoid the positive own-price elasticities. Note that to avoid over-specification, Friday and Week14 binary variables are omitted.

Consequently, the set of demand equations comprises nonlinear seemingly unrelated regression (NSUR), of which coefficients are estimated through iterated feasible general least squares (IFGLS). From the fitted demand equation, we would obtain the own-price (when i = j) and cross-price (when i ≠ j) elasticities for customer k on the day d with the relationship given as follows:

$$\varepsilon_{ijdk} = \frac{\partial E_{idk}/E_{idk}}{\partial PE_{jdk}/PE_{jdk}} = c_{ijk}\left(\frac{Y_{dk}}{PZ_m}\right)\left(\frac{PE_{jdk}}{E_{idk}}\right)$$

Hence, the price elasticity between period i and j of customer k is obtained by substituting the estimates $\widehat{c_{ijk}}, \widehat{Y_{dk}}$ into this equation with $PZ_m, PE_{jdk},$ and E_{idk} provided from the input data. Finally, given that each term of demand equati on is linear, this type of elasticity equation still hold after summation and averaging in customer k, period i or day d with respective energy use as weights. This yields the price elasticities aggregated in the industry level.

Results

Having completed the first stage of the analysis—construction of structural equations and CBLs—we are now intensively conducting the second stage of the research—econometric estimation of substitution elasticities. Given preliminary results we obtained so far, the CPP events indeed alter the load patterns of the Korean industrial and commercial customers formerly under the TOU rates with the average industry customer that exhibit greater response than the average commercial customer. There are substantial differences in demand response behaviors across and within the business sectors with the magnitude of response closely related to the sectors' expenditure shares of electricity. As far as between-day load shift is concerned, industrial customers seem to shift a significant amount of load to neighboring days, whereas, for commercial customers, no noticeable load shifting to neighboring days is observed. The econometric estimation of the substitution elasticities is underway.

Conclusions

A firm-level investigation we conducted so far clearly confirms wide-ranging differences in demand responsiveness across and within business categories. In the industrial sector, the metals, chemicals, rubber and plastics, wood, and paper segments seem to be highly price responsive, exhibiting conservation and shifting responses altogether. By contrast, metal ore mining, electronic equipment, other transport equipment, and water supply segments indicate slight or virtually no response. In the commercial sector, warehouse and sauna services seem to present the strongest response, whereas accommodations, real estate, and public administration and defense services remain nearly unchanged with the CPP events, which is largely consistent with earlier findings. Detailed and robust policy insights based on the fitted electricity demand functions will be derived, in combination with the analysis of several alternative CPP rate scenarios.

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