The Impact of Dynamic Pricing on Residential and Small Commercial and Industrial Usage: New Experimental Evidence from Connecticut

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Electricity cannot be stored economically in large quantities, and has to be consumed instantly on demand. The load duration curve for most utility systems is very peaky, with some eight to eighteen percent of annual peak load being concentrated in the top one percent of the hours of the year. And the costs of supplying electricity vary by time of day. Thus, the best way to price electricity is through time-varying rates.

Not only would this increase economic efficiency by closely reflecting the incremental cost of providing service, it would also eliminate inter-customer cross-subsidies that are embedded in flat rates. Of course, dynamic pricing can only be carried out once smart meters are in place. As of this writing, about a quarter of U.S. households are on smart meters and the number is projected to rise by the end of the decade to nearly a hundred percent. However, only one percent of the households are on any type of time-varying rate and only one percent of that one percent are on any form of dynamic pricing rate (Federal Energy Regulatory Commission (2012)).

Commissions and utilities continue to study the potential benefits of dynamic pricing through experimentation which provides an important avenue for gaining insights into the likely impact of those rates but: (1) most of it involves the residential sector; and (2) the majority of the experiments have been located in regions with hot and humid summers such as the District of Columbia, Florida, Illinois, Maryland, Michigan and Oklahoma. We add to that body of knowledge by: (1) presenting the results of a pilot in Connecticut which included small commercial and industrial (C&I) customers in addition to residential customers; and (2) examining the effects of time-varying rates in milder climates, such as New England, where the saturation of central air conditioning (CAC) systems is under 30 percent.

The pilot featured a time-of-use rate, two dynamic pricing rates and four enabling technologies. Customers were randomly selected and allocated to these rates, to ensure representativeness of the final results. The experiment included a total of around 2,200 customers and ran during the summer of 2009.

We find that customers do respond to dynamic pricing, a finding that matches that from most other experiments. Overall, we found that the elasticities of substitution, while smaller than those observed in warmer climates, are statistically significant. We estimate the elasticity of substitution for customers on critical peak pricing at -0.081. When dynamic pricing is offered with smart thermostats, the elasticity value is -0.128. The daily price elasticity is estimated at -.026, with or without enabling technology.

We also find that response to critical-peak pricing rates is higher than response to peak-time rebates. This finding contradicts the result found in the BGE pilot in Maryland during its first summer of operation in 2008, but is in line with the PowerCents DC pilot carried out by Pepco in the District of Columbia, which ran during the summers of 2008-09. This remains a topic for further research.

Like many other pilots, there is virtually no response to time-of-use rates with an eight hour peak period. And like the few pilots that have compared small C&I customer response to residential response, small C&I customers are less price-responsive than residential customers. While enabling technologies such as cycling of residential air conditioners notably boosts price responsiveness for customers on dynamic rates, the Energy Orb does not.

Within the subset of the residential customers who did respond to the income question, the price-response was essentially the same as those for the average customer with known income data. Using the second definition of low income, hardship status as certified by the state, the results were slightly different. In this case, results indicated that hardship customers responded slightly less than the average treatment customer to the critical-peak rate, although they did still respond. The incremental effect of the peak-time rebate rate was similar for hardship and non-hardship customers.