Energy Efficiency and Changes in Energy Demand Behavior

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ABSTRACT

This paper describes the results of a study that analyzes energy demand behavior in the residential, commercial, and industrial sectors. After defining what is meant by *energy demand behavior*, this paper describes the research design and findings related to the responsiveness of energy users, in aggregate, to market forces. These responses, expressed statistically as *elasticities*, are one way of measuring long-term market effects or the degree to which the markets for energy efficiency products and services have been transformed by energy efficiency policies. The evidence presented in this paper shows that energy efficiency policies have had the kinds of lasting effects on energy demand behavior that energy efficiency advocates find desirable.

Introduction

In a study recently published study (Horowitz, 2007 -- henceforth referred to as HORO-2007) a general model of electricity demand is applied to the U.S. commercial, industrial, and residential sectors. These models take into account virtually all of the U.S. electricity sales of the past three decades; in the entire U.S. in 2006, annual electricity sales amounted to 3.7 billion megawatt hours. According to EIA data, in this year the residential sector purchased 37 percent of total electric utility energy, the commercial sector purchased 35 percent, and the industrial sector purchased 28 percent of this total; less than one percent was purchased by the transportation sector. Another 147 million megawatt hours, or an additional 4 percent of electricity use, consisted of on-site generation used by the commercial and industrial sectors.

Several goals were accomplished in developing an electricity demand model that could be applied consistently across the three economic sectors, the 48 contiguous states, and the 27 years from 1977 through 2003. One goal was to use the model estimates to perform a counterfactual simulation of energy demand. The simulation provides answers to the question of what energy consumption would have been in states with strong or moderate commitment to energy efficiency programs *if* their responses to market forces were similar to those of states with weak commitment to energy efficiency programs. Using a difference-in-differences analysis across a base and a treatment period, the analysis resulted in estimates of the net impact of energy efficiency program commitment on electricity intensity and consumption in each sector.

Another goal in developing the electricity demand model in HORO-2007, and the focus of this paper, was to examine whether or not state-level commitment to energy efficiency programs may have caused long-term changes in energy demand behavior. *Program commitment*, measured on an ordinal scale, represents the extent of public agency, non-profit organization, and energy utility interest in energy efficiency within a state. The rankings, though admittedly imprecise, take into account reports of the impact of a state's programs, policies, or energy efficiency portfolio on state electricity savings. The terms *programs*, *policies*, and *portfolio* are used interchangeably to refer to collections of initiatives, some of which may involve voluntary program participation and others mandatory compliance with codes, standards, and regulations that operate in the same time period and same geographic location. Because a state's commitment may differ by market or consumer group, a state's commitment ranking is not necessarily the same for residential, commercial and industrial sectors.

What Is Energy Demand Behavior?

To appreciate the findings of this study, it is first necessary to understand what is meant by *energy demand behavior*. Applied economists study consumer behavior by creating and analyzing demand curves. A demand curve is typically drawn as a continuous and downward sloping curve in a two dimensional graph having a vertical (y) and a horizontal (x) axis. Although the visual interpretation of a demand curve may seem obvious -- prices up, purchases down; prices down, purchases up – there is much more to a demand curve than this initial observation. The size and shape of an actual curve, and where the curve is placed on the plane of the graph, have mathematical meanings. They express, in numbers, the relationships between different prices for a product (on the y axis) and the quantity of the product (on the x axis) that will be purchased at different prices. Knowing the size, shape, and placement of the curve is very useful; when relevant variables change, the demand curve can be used to predict changes in the market and changes in social welfare.

Unfortunately, producing actual market demand curves, rather than drawing stylized ones like those found in textbooks, is no easy task. Setting aside the difficulties in disentangling demand curve information from supply curve information, empirical data that document past prices and quantities are difficult to collect. Moreover, variations in consumer prices and quantities purchased, such as may occur over time and occur over place, are not sufficient for producing a market demand curve. A true demand curve, in the economic sense, is not merely a line drawn through points made up of discrete pairs of price-quantity data. Other important demand-related market factors must be considered, making the task of analysis more difficult than the task of data collection.

By definition, a demand curve is isotemporal and isolocational. This means that all the points along a demand curve are intended to express a price-quantity relationship that exists at the same moment in time and at the same defined location. In other words, despite its simple geometric appearance, an actual demand curve is a statistical construct that can rarely be created from empirical measurement of the two principal variables alone. Time-varying or location-varying price and quantity data, or a combination of the two, though necessary, are not sufficient for estimating an actual market demand curve. Why this is so can easily be seen by graphing price-quantity data only. Not uncommonly, a plot of price-quantity data at different times in the same location will yield an upward sloping time trends, and a plot of price-quantity relationships at different locations and the same time will yield a random scatter. Neither of these graphs will be related to a demand curve.

The problem with using time trend data for a single location is that many factors that are related to product prices and quantities vary over time, too. The prices of substitutable products may change, or the affluence of consumers may change, to name just a few variables. Likewise, factors related to product prices and quantities for a single time at different locations may differ, such as climates or population sizes. Only if time-related factors can be controlled for can time trend data be molded into an isotemporal demand curve; and only if location-related factors can be controlled can locational price-quantity data be molded into an isolocational demand curve. In short, additional variables and statistical processing are required to estimate a demand curve from actual price and quantity data. As a side note it might be mentioned that there are other ways of estimating demand curves that do not require observed historical data. One approach is to use consumer survey data to determine, by structured questioning, what quantities of a product consumers say they will purchase at different prices. However, these artificial approaches have familiar, well-documented limitations. They tend to be used in situations where there are no historical data, such as for studying how new products may fare, or for valuing public goods.

In estimating a demand curve from historical data, the focus is on explaining variations in the quantity purchased of a product. Regression models are used for this purpose. Using a regression model, variables chosen to explain variations in the quantity purchased do two things. First, they control for, or hold constant, the phenomenon they represent, permitting other explanatory variables that may be in the analysis to be viewed as autonomous influences on quantity purchased. Second, in receiving from other explanatory variables the reciprocal benefit, they reveal how the quantity purchased varies with a marginal change in their own values, exclusive of other influences. When the bilateral relationship between quantity purchased and an explanatory variable is expressed as a small or marginal *percentage* change in the explanatory variable leading to a given *percentage* change in the quantity purchased, it is referred to as an *elasticity*.

Although long lists of variables that may be believed to influence the quantity purchased of any product may be drawn up, no demand analysis can, or should, embrace all conceivable explanatory variables. Practically speaking, historical data are usually not available for all the minor factors that may occasionally sway, or may merely be correlated with, demand. Moreover, once several variables that together contain a large share of the explanatory power are included in an analysis, adding more variables can be superfluous, if not counterproductive. Inclusion of minor variables may not only lead to a loss of precision, but to misinterpretation if the minor variables are proxies for different, underlying variables.

In economic studies, usually the most critical variables to include in an analysis of quantity demanded are the price of the product, the price of its closest substitute, and the income or wealth of the consumers of the product. The elasticities associated with these variables are called price elasticity, cross-price elasticity, and income elasticity. Price elasticity expresses how a marginal percentage change in a product's price affects, in percentage terms, the quantity purchased; cross-price elasticity expresses how a marginal percentage change in the price of the product's substitute affects, in percentage terms, the quantity purchased; and, income elasticity expresses how a marginal percentage change in consumer income affects, in percentage terms, the quantity purchased. Each of these characterize different aspects of demand behavior. They summarize the economic behavior of the representative consumer.

Once estimated using the appropriate regression model specification, functional form, and estimator, each elasticity, or all of them together, can be used for analysis and prediction. Of course, like with all statistical inferences, assumptions must be maintained about the data, the model, causality, and the context under which the inference is drawn. One assumption that is particularly relevant to the study of energy efficiency programs and energy use is that market demand elasticities, typically thought of as those of the *representative consumer*, do not change under the influence of the energy efficiency programs, policies, or portfolios.

This assumption about the deep behavior of the representative consumer, i.e., that energy demand elasticities are stable, is the center of attention of this paper. How stable are these parameters in the face of policies that are in meant to change them? It stands to reason that if a program portfolio targeted at a group of consumers is effective, it should eventually, if not immediately, change the demand behavior of these consumers. Indeed, it may even change the demand behavior of consumers that are not in the targeted group. The former is what might be called a direct, long-term *market effect,* and the later is what might be called an indirect market effect, a positive externality, or *spillover*. Furthermore, to the degree that the intensity of program commitment varies and produces more uncertainty in the market than may otherwise exist, it is to be expected that this, too, could change the long-term behavior of consumers.

If a state's program commitment does indeed alter long-term demand behavior, it is possible that many of the methods currently used to evaluate energy efficiency programs may lead to biased and inconsistent estimates of program impacts. For example, studies that use relatively short pre and post-participation periods, or simple participant/non-participant comparisons over short periods of time, will fail to account for permanent shifts in demand that are attributable to energy efficiency policies. This could undermine the cost-effectiveness of programs whose goals are, in fact, to influence long-term energy demand behavior. Addressing this problem requires a new kind of impact evaluation, ones that measure market transformation by analyzing long-term changes in economic behavior. Since demand-related economic behavior is measurable through consumer responses to market forces, these changes should be detectable by analyzing the changes of market demand elasticities. Indeed, in perhaps the first energy efficiency market transformation study to ever explore this phenomenon (Horowitz, 2001), a significant change attributable to energy efficiency programs was found in the price elasticity of demand for fluorescent lighting ballasts.

To summarize, since many energy efficiency policies are intended to produce long-term changes in energy demand behavior, it stands to reason that in addition to measuring short term changes in energy use, impact evaluations ought to be designed to measure changes in energy demand behavior. This can be done by estimating and analyzing demand curves, since by simultaneously taking into account the influence on demand of several variables demand curves are, in fact, complex representations of energy demand behavior.

Research Design and Findings

In HORO-2007, an electricity intensity model is specified using a uniform set of variables and a common functional form for all three sectors. The independent variables for each sector are, respectively, the average retail price of electricity (*P*); the average retail price of natural gas (*N*); state economic status as captured by per capita income or GSP (*G*); climatic conditions, i.e., heating (*H*) and cooling (*C*) degree days; and lastly, a time trend related to technological change in each sector (*T*). Technology trend data are from the Federal Reserve Board and are sector-specific. For example, for the commercial sector, market group index B52120 is employed; it represents the production of products that are more closely associated with the business world such as information processing and related equipment. The general function is:

$$EI_{t,i,R} = f(P_{t,i,R}, N_{t,i,R}, G_{t,i,R}, H_{t,i,R}, C_{t,i,R}, T_{t,R})$$

in which subscript *t* represents a given year; subscript *i* represents a given state; and, subscript *R* represents a discrete level of commitment to energy efficiency policies. This split-case function asserts that *R* influences each of the behavioral relationships associated with electricity intensity. In other words, *R* is a transformative agent. To identify *R*, a variety of quantitative and qualitative sources were consulted, resulting in a ranking of the 48 states into quartiles -- one strong (*S*) , two moderate (*M*), and one weak (*W*) -- based on a general indicator of statewide support and encouragement of energy efficiency programs. Given the imprecise measurement of *R*, the highest degree of contrast between in energy demand behavior is expected to be between the *S* states and the *W* states, leading models of the form:

$$EI^S = \beta_0^S + \sum_{j=1}^n \beta_j^S X_j^S + u^S$$

for the strong states and the analogous,

$$EI^W = \beta_0^W + \sum_{j=1}^n \beta_j^W X_j^W + u^W$$

for the weak states. In these models, the superscript *S* represents states that fall into the strong program commitment quartile and the superscript *W* represents states that fall into the weak program commitment quartile, the β_j's are the coefficients associated with each of the X_j independent variables, and the *u*'s are independent error terms.

To heighten the contrast in *R*, within this split-case research design, two distinct time periods are defined. In the early or base period, meaning the years from 1977 to 1991, many states experienced either no programs at all or the very beginnings of programs. In the latter period, 1992 to 2003, a small number of states had aggressive, mature energy efficiency programs, a larger number had newer programs, and a small number continued to have little or no involvement with energy efficiency programs. Although the cutoff between periods is inaccurate for individual states, it is practical for a variety of important reasons. For one, it was the first year in which a major, new national energy policy, the Energy Policy Act of 1992, took effect. For another, it was the first year in which large scale national programs like the Environmental Protection Agency's Green Lights and ENERGY STAR became operational.

With two contrasting levels of *R* between states, and two contrasting levels of *R* between years, multiple comparisons of energy demand behavior are possible. In Table 1, behavior, as represented by elasticities, is compared between quartiles in the base period and in the treatment period for three of the six independent variables in the electricity intensity model, i.e.,, electricity price, per capita GSP (or personal income for the residential sector), and a time-varying but state-constant technology trend that is specific to each sector. The three omitted elasticities are those of the less important and generally not statistically significant variables representing annual state natural gas prices and heating and cooling degree days.

Table 1 shows the magnitudes, and differences, of the elasticities between quartiles (since the elasticities are expressed in logarithms, the differences between them are interpretable as percentages). Alongside the percentages are comments reflecting the desirability of the behavioral differences from the perspective of energy efficiency program advocates. For example, from the perspective of energy efficiency advocates, it should be more desirable that a 10 percent increase in electricity price lead to a six-and-one-half of a percent *decrease* in electricity demand, than it is that it lead to a seven-and-seven-tenths of a percent *increase* in demand. This, as can be seen in Table 1 in the row containing the commercial sector elasticities in the base period, is noted as "S Superior" in the column marked "Behavior." Turning to the income effect and using an example from the residential sector in the base period, it should be more desirable that a 10 percent increase in per capita income lead to a 2.3 percent *increase* in electricity demand, than it is that it lead to a 4.7 percent *increase* in demand. This is noted as "S Inferior" in that the behavior of the *S* quartile is less desirable than the behavior of the *W* quartile. Lastly, turning back to the commercial sector – only now in the treatment period -- the elasticities indicate that a 10 percent increase in the technology time trend will lead to a two-and-seven tenth of a percent *increase* in electricity demand in the *S* quartile, and to a one-and-eighttenths of a percent *increase* in demand in the *W* quartile. This difference is rather small, and hence “Similar” is noted in the behavior remarks.

Table 1: Comparison of Elasticities Between Quartiles in Base and Treatment Periods

Sector/ Variables	Base *S*	Base *W*	ln % (*S*-*W*)	Behavior (Elasticity)	Treatment *S*	Treatment *W*	ln % (*S*-*W*)	Behavior (Elasticity)
Commercial								
Electricity Price	-0.065	0.077	-14%	S Superior	-0.204	-0.219	1%	Similar
Per Capita GSP	-0.590	-0.545	-4%	Similar	-0.937	-0.361	-58%	S Superior
Technology Trend	0.074	0.170	-10%	S Superior	0.027	0.018	1%	Similar
Industrial								
Electricity Price	-0.204	-0.433	23%	S Inferior	-0.588	0.234	-82%	S Superior
Per Capita GSP	-0.847	0.033	-88%	S Superior	-0.385	-0.743	36%	S Inferior
Technology Trend	0.157	-0.131	29%	S Inferior	0.005	0.186	-18%	S Superior
Residential								
Electricity Price	-0.237	-0.222	-1%	Similar	-0.519	-0.384	-14%	S Superior
Per Capita Income	0.470	0.233	24%	S Inferior	0.161	0.150	1%	Similar
Technology Trend	0.036	0.112	-8%	S Superior	0.008	0.015	-1%	Similar

Without describing every single finding in Table 1, a few general comments on between-group differences are worth pointing out. In the commercial sector, the behavior of the *S* quartile is superior on two of the three behavioral dimensions in the base period, but only one of the three dimensions in the treatment period. From these findings it might be speculated that the desirable behavior of the *W* quartile has improved, or conversely, that the behavior of the *S* quartile has become more undesirable. In the industrial sector, it appears that the *S* quartile exhibited more less desirable behavior than the *W* quartile in the base period, and then shifted to more desirable behavior than the *W* quartile in the treatment period. Again, whether or not this represents progress on the part of the *S* quartile, or backsliding on the part of the *W* quartile, remains to be discovered. Finally, in the residential sector, the behavior of the two quartiles is mixed, making it difficult to draw any conclusions.

Much of these interpretive difficulties in these comparisons can be resolved by comparing the elasticities within quartiles and across periods, rather than between quartiles in the same period. In Table 2, the same findings are recast to show how the energy demand behavior of the quartiles changed from the base to the treatment period. Viewed this way, the *S* quartile shows more improvement than the *W* quartile in the commercial and industrial sectors, but not in the residential sector. This implies that:

- in the commercial sector, the *S* quartile began by exhibiting more desirable energy efficiency behavior than the *W* quartile, and while their behavior improved in the treatment period, so too did that of the *W* quartile. Together, these findings suggest that the energy efficiency commitment of the *S* quartile not only had long-term impact on their own energy demand behavior, but had a positive impact on the energy demand behavior of the states within the *W* quartile;
- in the industrial sector, the *S* quartile began by exhibiting less desirable energy efficiency behavior than the *W* quartile, but their behavior improved in the treatment period, while

that of the *W* quartile worsened. These findings suggest that the energy efficiency commitment of the *S* quartile had a long-term impact on their own energy demand behavior, and little if any positive impact on the energy demand behavior of the states within the *W* quartile; and,

- in the residential sector, both the *S* quartile and the *W* quartile exhibited improved energy demand behavior across all three dimensions. This suggests that the energy efficiency commitment of the *S* quartile not only had long-term impact on their own energy demand behavior, but had a positive impact on the energy demand behavior of the states within the *W* quartile.

Table 2: Comparison of Elasticities Between Periods, by Quartile

Sector/ Variables	***S* Quartile Base**	**Treatment**	**ln % (B-T)**	**Behavior (Elasticity)**	***W* Quartile Base**	**Treatment**	**ln % (B-T)**	**Behavior (Elasticity)**
Commercial								
Electricity Price	-0.065	-0.204	14%	Improved	0.077	-0.219	30%	Improved
Per Capita GSP	-0.590	-0.937	35%	Improved	-0.545	-0.361	-18%	Worsened
Technology Trend	0.074	0.027	5%	Improved	0.170	0.018	15%	Improved
Industrial								
Electricity Price	-0.204	-0.588	38%	Improved	-0.433	0.234	-67%	Worsened
Per Capita GSP	-0.847	-0.385	-46%	Worsened	0.033	-0.743	78%	Improved
Technology Trend	0.157	0.005	15%	Improved	-0.131	0.186	-32%	Worsened
Residential								
Electricity Price	-0.237	-0.519	28%	Improved	-0.222	-0.384	16%	Improved
Per Capita Income	0.470	0.161	31%	Improved	0.233	0.150	8%	Improved
Technology Trend	0.036	0.008	3%	Improved	0.112	0.015	10%	Improved

Discussion and Conclusion

Despite the attempt to foster as much contrast as possible for the comparisons across study quartiles and study periods, it should be noted that the imprecision in state commitment rankings, and the imprecision in the uniformly-imposed cutoff year between periods, are individually and collectively likely to bias the findings downwards. Simply put, the blurrier each of the contrasts, the more the effects of program commitment will go undetected or under-detected. This could be one reason why even sharper differences between quartiles were not to be found.

Alternatively, it is possible that the national influence of states with strong energy efficiency program commitment is sufficiently powerful that regardless of state rankings and cutoff year precision, sharper differences between quartiles could simply never be found. Spillover of such magnitude is obviously something that would be highly desirable to energy efficiency advocates, which makes it all the more imperative that in-depth studies of changes in long-term energy demand behavior find a place on state and national impact evaluation agendas.

To conclude, the assumption that demand elasticities are stable, *is at the center of the issue of market transformation or market effects*. As stated previously, it stands to reason that if an energy efficiency program portfolio targeted at a group of consumers is effective, it should eventually, if not immediately, change the aggregate behavior of these consumers. Indeed, it may even change the behavior of consumers that are not in the targeted group, as well as the behavior of producers. All of these changes may be considered *the market effects of energy efficiency programs*. The existence of these changes, and their magnitudes, direction, and statistical significance are empirically testable by estimating and studying demand curves.

This analysis shows one of the ways in which economic theory and econometric theory give clear guidance as to how to empirically study the market effects of public policies. There are many more issues that economic theory addresses, such as when and how to treat variables as exogenous and endogenous, how to distinguish stock and flow effects, and how to differentiate the costs associated with different product features, to name just a few. Thus far, few such studies exist.

References

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