Econometric Methods for Estimating ENERGY STAR Impacts in the Commercial Building Sector

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ABSTRACT

The early stages of developing a national impact evaluation of EPA's ENERGY STAR for the commercial building sector are described in this paper. Being broad in geographic scope and time-frame there are numerous research issues that this study raises, such as how to account for the impacts of local public programs and how to control for economy-wide trends that could affect energy use. The methodology described in this paper involves identifying and quantifying the major economic and physical factors that determine energy use, such as principal business activities, energy prices, investments in specialized stocks of capital equipment, and climate. When completed, in addition to providing program evaluation findings, this study will yield useful side benefits, such as updated energy price elasticity estimates needed by economists, environmentalists and energy forecasters.

Introduction

EPA's ENERGY STAR® is national in scope, comprehensive in design, ambitious in purpose, and bound to be around for a long time. It is endorsed, supported and sustained by the U.S. Congress. In the commercial buildings sector, ENERGY STAR's activities include voluntary partnership agreements and outreach activities for big and small businesses, tools for comparing energy use across buildings and for linking best energy management practices to financial performance, and national awareness campaigns. Every commercial building, in every state, could be influenced by these activities, be it an ENERGY STAR labeled building, a casual participant, or neither.

How is it possible to measure the national environmental protection impacts of this multi-faceted program? This paper describes a methodology that is in its development stages for estimating the changes in commercial building energy use that can be attributed to ENERGY STAR. The methodology first entails identifying the major economic and physical factors that determine energy use, such as principal business activities, energy price elasticities, investments in specialized stocks of capital equipment, and climate. Separately and collectively, the variables suggest a number of different modeling options.

Complicating matters further, many other local public programs are currently helping to improve and expand the markets for commercial sector energy efficient products and services. Many of these programs are, in different forms, market transformation programs, loosely defined as publicly-funded activities that promote enduring pro-energy efficiency behavior. The challenge of this study is to estimate ENERGY STAR accomplishments while taking into account the accomplishments of these other public programs.

Data Issues

To estimate the climate protection impacts of ENERGY STAR for the commercial buildings sector a dataset has been constructed consisting of building level microdata and regional and national level data. The building data are derived from U.S. Energy Information Administration's (EIA) Commercial Buildings Energy Consumption Survey (CBECS), a national survey undertaken in 1986, 1989, 1992, 1995 and 1999. As yet, the CBECS 1999 survey data are not published. When they are, they will be incorporated into the existing ENERGY STAR impact evaluation dataset. Regional and national data in the dataset for the CBECS survey years are derived from various federal agency data sources, including the U.S. Census Bureau and the Federal Reserve Board.

Over the past fifteen years, many trends in society and the economy have affected energy use in the commercial sector. In addition to changing prices for energy and other energy-using equipment, energy use has been influenced by such forces as increasing affluence, new technologies and public programs. As such, the aim of this study is to identify and control for the major factors that have driven commercial building energy use over the past 15 years. By doing so, energy use trends related to public programs such as ENERGY STAR may be differentiated from energy use trends that are strictly the result of market forces.

To accomplish this objective a preliminary pooled cross sectional econometric model of energy demand has been specified and estimated. For understanding the rationale behind the modeling effort it is useful to briefly describe the theory underlying energy demand. To begin, energy is not a good which is demanded for its value in and of itself. Rather, it is demanded as an input to equipment and appliances to produce end uses or services such as light and warmth. Since energy consumption occurs in conjunction with a stock of capital, its demand is *derived* from the demand for the services which the capital provides. Energy consumption can thus be represented by the identity:

$$Q_i = \sum_{k=1}^{M} R_{ki} A_{ki}$$

where total consumption of a given fuel i is the sum of fuel consumed by each type of capital equipment, A, in conjunction with utilization rate R_{ki} for the k^{th} type of equipment and i^{th} type of fuel. The behavioral relationships between the demand for capital equipment and the derived demand for energy can be identified separately such that:

$$A_i = f(P_i, P_j, P_a, Y, X); \quad i \neq j$$
$$R_i = g(P_i, Y, Z)$$

where the demand for equipment using fuel i depends on the price of fuel i, the price of alternative fuel j, the price of equipment P_a, consumer income or total building expenditures Y, and lastly, a vector of other variables X. In theory, the utilization rate of fuel i for a given unit of equipment depends on its own price, income, and a vector of other variables Z.

In the CBECS databases, information on the building's equipment stock is limited. Merging the equipment demand model with the utilization rate model results in an energy demand model for fuel i:

$$Q_i = h(P_i, P_j, Y, X, Z, A)$$

where A is a vector of equipment stock which, unlike in the initial energy demand identity above, is not tied to end use consumption. The vectors of other variables, X and Z, play important roles in this model. For the present study, they include two kinds of factors that influence trends in building energy use. These are building-specific factors such as a buildings' principal building activity and general economic factors both at the census division and national levels, such as per capita income.

Energy Impact Models

At present, in the absence of the 1999 CBECS survey, a preliminary analysis has been completed of the four earlier CBECS with the intention of updating the analysis once the most recent CBECS data are available.

Among the many varieties of energy utilization functional forms models that can be estimated, perhaps the most useful one for the ENERGY STAR evaluation focuses on electricity use, electricity production being the single largest source of building-related greenhouse gas emissions. Therefore, the preliminary analysis of the CBECS data entails estimation of an energy demand model taking *electricity energy use intensity index,* or *KWHEUI*, as the dependent variable. This index is calculated as total annual building electricity use divided by building square feet. One of the key advantages of this index is that it normalizes building consumption, thereby reducing, but not eliminating, building scale effects. Suppressing subscripts related to regional location and year of survey, the model of a building's energy consumption takes the general form:

$$\begin{aligned} KWHEUI &= b_0 + b_1 P' + b_2 WEATHER' + b_3 BLDG' + \\ &\quad b_4 EQUIPMENT' + b_5 USAGE' + b_6 PBA' + b_7 TIME' + e \end{aligned}$$

where each term represents a vector of variables and associated coefficients. For example, *WEATHER'* consists of two variables, i.e. heating degree days (HDD) and cooling degree days (CDD) calculated at base 65, and *PBA'* represents thirteen different principal business activities, or building types, as identified in CBECS. Since every CBECS sample was independent of every other one, there is only one data point per surveyed building in the sample.

It is important to note that the composition of the building sample vis-à-vis building fuel systems must be explicitly taken into consideration in estimating unbiased model parameters. The CBECS survey documents the use of four major fuels that are commonly consumed in commercial building. These are electricity, natural gas, fuel oil and steam. To control for the fact that energy use behavior will differ in buildings with different combinations of fuels, if for no other reason than differences in relative fuel prices, separate models must be developed for each building/fuel system combination.

The model presented in Table 1 is for buildings with electricity and natural gas systems, only. This first group of buildings makes up approximately fifty-five percent of the CBECS sample. The second group largest group of buildings is one with electricity use, only. This group makes up another 24 percent of the CBECS sample. The model for these buildings is presented in Table 2. In both tables, PBA-specific fixed coefficients are suppressed.

Table 1. Energy Demand Model: Electricity and Natural Gas Systems Dependent Variable = LOG(KWHEUI)

Variable		Coefficient	Std. Error	t-Statistic	Prob.
C	b_0	-10.31284	1.126739	-9.152824	0.0000
LOG(EL$R)	b_{1a}	-0.913169	0.032177	-28.37994	0.0000
LOG(NG$R)	b_{1b}	-0.074616	0.032141	-2.321512	0.0203
LOG(HDD)	b_{2a}	-0.102725	0.016140	-6.364467	0.0000
LOG(CDD)	b_{2b}	0.085253	0.012628	6.751123	0.0000
LOG(SQFT)	b_{3a}	-0.415111	0.009890	-41.97354	0.0000
LOG(AGE)	b_{3b}	-0.198179	0.013064	-15.16975	0.0000
EMS	b_{4a}	0.150238	0.020850	7.205633	0.0000
SOLAR	b_{4b}	0.197655	0.166147	1.189642	0.2342
HPMP	b_{4c}	0.073678	0.026108	2.822022	0.0048
LOG(WEEKHR)	b_{5a}	0.441736	0.021149	20.88647	0.0000
LOG(WORKRS)	b_{5b}	0.372321	0.009391	39.64670	0.0000
MAINT	b_{5c}	0.164147	0.018358	8.941294	0.0000
VCNCY3	b_{5d}	-0.104991	0.019447	-5.398812	0.0000
NGINTRP	b_{5e}	0.060618	0.034398	1.762240	0.0781
LOG(EARNJOBR)	b_{7a}	1.227444	0.102269	12.00216	0.0000
Y95	b_{7b}	-0.108344	0.024925	-4.346755	0.0000
Y92	b_{7c}	-0.034820	0.023341	-1.491784	0.1358
Y89	b_{7d}	0.025357	0.022151	1.144755	0.2523
Adjusted R-squared		0.486			
n of observations		10,414			

The energy demand models are estimated in double-log form using ordinary least squares and the White heteroskedasticity correction. Due to the particular quality and features of the CBECS surveys, several data screens were imposed on the microdata. Among the most important of these were that buildings reporting their size as larger than one million square feet were dropped, as were buildings with unusually small or large electric energy intensity. Building types are categorized in conformance with the CBECS definitions, with the exception being that for this study warehouses are differentiated by whether or not they are refrigerated. The default building type is what CBECS designates as 'other' and buildings designated as 'vacant' are excluded from the dataset. Nominal dollar values are adjusted to 1992 dollars using the consumer price index.

Table 2. Energy Demand Model: Electricity System, Only Dependent Variable = LOG(KWHEUI)

Variable		Coefficient	Std. Error	t-Statistic	Prob.
C	c_0	-17.20313	2.162896	-7.953747	0.0000
LOG(EL$R)	c_{1a}	-1.222380	0.054084	-22.60156	0.0000
LOG(HDD)	c_{2a}	-0.001829	0.018194	-0.100511	0.9199
LOG(CDD)	c_{2b}	0.114655	0.023393	4.901323	0.0000
LOG(SQFT)	c_{3a}	-0.388476	0.014709	-26.41122	0.0000
LOG(AGE)	c_{3b}	-0.103517	0.023620	-4.382579	0.0000
EMS	c_{4a}	0.218905	0.037002	5.916080	0.0000
SOLAR	c_{4b}	-0.349178	0.238365	-1.464887	0.1430
HPMP	c_{4c}	-0.018267	0.027005	-0.676425	0.4988
LOG(WEEKHR)	c_{5a}	0.459851	0.031895	14.41746	0.0000
LOG(WORKRS)	c_{5b}	0.302413	0.013431	22.51671	0.0000
MAINT	c_{5c}	0.245688	0.029458	8.340175	0.0000
VCNCY3	c_{5d}	-0.124733	0.029708	-4.198619	0.0000
LOG(EARNJOBR)	c_{7a}	1.686530	0.194579	8.667589	0.0000
Y95	c_{7b}	-0.281056	0.037777	-7.439954	0.0000
Y92	c_{7c}	-0.148113	0.036863	-4.017983	0.0001
Y89	c_{7d}	-0.055456	0.036096	-1.536348	0.1245
Adjusted R-squared		0.473			
n of observations		4,419			

In brief, the energy demand model for electric and natural gas consumers in Table 1 indicates the following:

- the long-term demand for electricity is approximately unit elastic and the price of natural gas has little effect on the demand for electricity.
- the coefficient of the HDD variable is negative, indicating that electric energy intensity decreases with weather severity.
- building size is negatively related to electricity intensity, indicating that building scale effects remain important to consider even after whole building energy use has been normalized by square footage.
- building age is negatively related to electricity intensity, and of the three types of energy efficient equipment in the model, the coefficients of energy management controls systems and heat pumps are statistically significant.
- four of the five building use-related variables are statistically significant; longer hours and more workers are associated with higher building electricity intensity and a vacancy of more than three months is associated with lower electricity intensity. Like the energy efficiency features, a building maintenance program is associated with higher electricity intensity. According to the model, electricity intensity is not statistically significantly different for those buildings that are on a natural gas interruptible rate schedule compared to those that are not on such a schedule.

- a marginal change in average earnings per employee across census divisions is associated with a 1.2 percent increase in energy intensity. This variable incorporates an aggregate *income effect* reflecting regional economic conditions.
- the time trend variable indicates that electricity intensity did not fall appreciably between 1986 and 1992, but did fall noticeably from 1986 to 1995.

In the alternate version of this model for buildings that use electricity, only, presented in Table 2, many of the coefficients of the independent variables in this model are similar in sign and magnitude to those of the prior model. Two notable differences in this model are (a) moderately higher estimates of the price elasticity of electricity demand and the earning elasticity of demand and (b) a statistically significant drop in electricity intensity between 1986 and 1992, as well as between 1986 and 1995.

Although the explanatory powers of these models appears to be moderately good, several complications are present. One issue is suggested by the theory underlying energy demand, namely that the demand for energy-related equipment, such as energy management and control systems, heat pumps and solar energy is at least partially influenced by a building's energy intensity. In other words, these explanatory variables may be endogenous or correlated with the energy demand model's error term. Preliminary exploration of this issue has been undertaken through the construction of various instrumental variables. However, tests of these instrumental variables have thus far indicated that they are relatively weak. It is therefore best to assume, for the time being at least, that the demand for this type of equipment is less affected by overall building energy intensity than it is by other non-energy related factors.

Another important issue that these models do not address is the effect of public policies, such as electric utility demand side management (DSM) programs within each census division, on the trend in energy use. To partially address this issue, data related to commercial program DSM savings can be incorporated into the model. However, there remain other public programs that must also be accounted for.

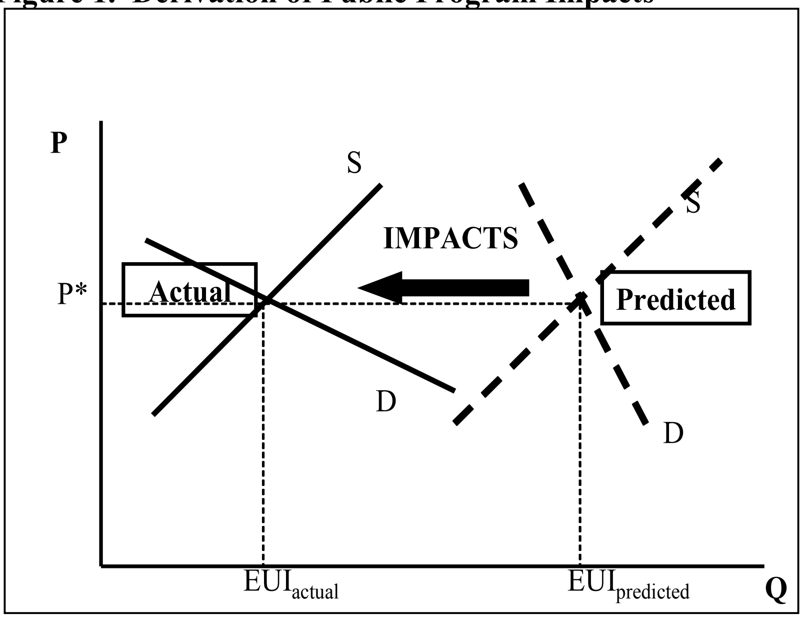
Estimation of Program Impacts

This model framework provides a basis for statistically modeling annual building energy consumption with pooled data from the five CBECS surveys. Once an appropriate model is developed it may be used to forecast average building energy consumption in future years. A comparison between actual energy consumption and the forecasted energy consumption may then provide as estimates of the public program effect. The quantified effect can then be translated into national energy savings, and ultimately, climate protection impacts.

For example, using the econometric model provided in Table 1, suppose that this model has been estimated using all but the last CBECS dataset. Then, taking the most recent CBECS dataset, the energy use of all of the buildings that are represented by a particular model, i.e., all of the buildings with electric and natural gas use, are forecasted using the observed values of each building's independent variables.

In Figure 1, the average predicted energy use for these buildings is the point of market equilibrium occurring at the intersection of the dashed supply and demand curves on the right hand side of the figure. This estimate can be compared to the average actual energy use of these buildings, portrayed as the market equilibrium formed by the intersection of supply and demand at the left of the figure. Note that the equilibrium energy price is held constant to emphasize that the forecast is based on the actual values of the independent variables for a given building. Since the model is designed to control for market forces and building-specific features, the difference between the average energy use that was predicted to be occur due to market forces and building specific features, and the average energy use that actually occurred is, by inference, the total non-market or public program effect.

Figure 1. Derivation of Public Program Impacts



As the full public program effect incorporates more than EPA's ENERGY STAR impacts, the ENERGY STAR evaluation must account for several other public programs and policies at the federal, regional, and statewide levels that may not be controlled for in the model itself. For the most part, the most effective approach to accounting for the many smaller programs is via adjustment of the total public program effect using published sources of program information. Many of these published estimates may be taken at face value, while others may require refinement based on additional analyses.

Conclusion

This paper has provided an overview, and illustrations, of the work that is going into developing the first national-level program impact evaluation of EPA's ENERGY STAR for the commercial building sector. As the discussions in this paper reveal, there remain many technically difficult issues to negotiate before this work can be completed. These issues include the functional form of the econometric model(s), the level of data aggregation, and issues related to specific endogenous and exogenous variables.

Despite the technical obstacles, the econometric approach to estimating the market transformation effects of EPA's ENERGY STAR appears promising. As EIA's CBECS remains a unique source for national building consumption and building characteristics data, this approach offers the possibility of conducting ongoing and periodic commercial sector program evaluations. Also, it suggests that there may be many other energy efficiency programs, including those sponsored at the state and regional level that may be able to take advantage of the insights and innovations of the present study to conduct future program evaluations with minimal data collection costs. Finally, in addition to providing program evaluation findings, this study offers useful side benefits, such as updated energy price elasticity estimates needed by economists, environmentalists and energy forecasters.