Measuring New-Construction DSM Program Net Energy Savings: A *Type-Casting* Approach

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In this study we present a new method for measuring new-construction gas and electric energy conservation program effects. This method, called *type-casting,* is a generalization of the conditional demand technique. The analysis we present in this paper is somewhat unusual in that we propose an approach of *directly* modeling what would have happened in the absence of the program. This is in contrast to the use of the traditional comparison-group proxy variables, such as nonparticipants. We apply this method to the evaluation of a utility-sponsored new-construction program. The method can, however, be applied to a wide range of DSM program.

The *type-casting* technique allows us to estimate energy usage equations employing information about newly-constructed *and* older buildings for our evaluation. For buildings constructed by program participants we use these equations to quantify the extent to which energy consumption by the occupants is lower than we would have expected if the program had not existed. In this case we estimate the program impact net of the free-rider effect.

For buildings constructed by the nonparticipants we also quantify the extent to which energy consumption by the occupants is lower than we would have expected if the program had not existed. In this case we estimate the free-driver/spillover effect of the program.

The *type-casting* method is an econometric technique that can account for the underlying engineering (thermodynamic) relationships and does not rely upon claimed behavior by builders or building occupants.

Introduction

In this paper we introduce a new method for estimating DSM program savings using data that were generated in the presence and the absence of the program. This method, called *type-casting, is* a generalization of the conditional demand technique. The general idea of the *type-casting* method is to categorize buildings into two types: participant and nonparticipant, and to analyze program impacts *separately* for occupants of each of these types of buildings. This *method is of particular interest when we are making use of subsamples in which we cannot classify the subjects as definitely participants or nonparticipants.*

The analysis we present in this paper is unusual in that we propose an approach of *directly* modeling what would have happened in the absence of the program. This is in contrast to the use of the traditional comparison-group proxy variables, such as nonparticipants. We apply this method to the evaluation of a utility-sponsored new-construction program. The method can, however, be applied to a wide range of DSM programs.

A key aspect of the analysis is that it combines an analysis of builder participation decisions with an analysis of general trends in building practices and the effects of building construction standards. This modeling approach is designed to be implemented using energy consumption and survey data to compute an estimate of what consumption would have been in the absence of the program for the market segments of interest. Thus, a very important aspect of the *type-casting* method is that it is focused upon obtaining meaningful base-case comparison groups. The comparison group issue is important because the proposed method is designed to measure the net rather than the gross impact of the program.

The idea is that there might be underlying regularities in the types/locations of buildings that help determine whether the builder chooses to participate in the program. There are economic arguments that suggest that the highest builder participation rates would be for the types of buildings/locations that would gain the most energy savings from conservation. Of course, there may be no such regularities. Even if there are regular patterns that are associated with program participation, it may be that the buildings built by the two groups would not have differed substantially in the pre-program period. In this case, as will be shown, the savings impact computation would be somewhat simplified.

In the remainder of this discussion I will first describe the *type-casting* method for obtaining base-case energy usage estimates and then propose a general approach that can be used to calculate net program savings from these estimates. After this I will give an example of a program impact calculation; and conclude the main portion of the paper with a summary of the main ideas, a description of the data requirements for the analysis, and a short review of some alternative approaches.

Type-Casting Energy Usage Equations

In this section, I describe the segmented conditional demand regression that are used to estimate equations for energy usage by participants and nonparticipants in the presence and the absence of the new construction program. Using this approach, we segment the conditional demand equation into four subequations for program participants and nonparticipants in the presence and absence of the program. These energy usage estimates are then used to calculate program savings for participants that are net of free rider effects. In addition, these estimates are used to calculate free-driver/spillover effects for program nonparticipants.

Taking into account possible differences between the performance of participant and nonparticipant buildings, the expected value of energy use, e, for a customer is:

$$E(e) = E(e_N)\ P_N + E(e_R)\ P_R \tag{1}$$

where E(e) is the overall expected value of energy consumption, $E(e_N)$ is the expected value of energy consumption for program nonparticipants, P_N is the probability of being a program nonparticipant, $E(e_R)$ is the expected value of energy consumption for program participants, and P_R is the probability of being a program participant. Since we have two[1] exhaustive and mutually exclusive categories, $P_R = 1 - P_N$.

We use this orientation to specify an estimating equation that can be used in evaluating a new-building construction program. The general idea is to obtain an instrumental variable estimate of the probability of being a program participant, P'_R, and to employ this variable in estimating a segmented conditional demand equation, using a data set that includes buildings built before and after the program began.

The term *type-casting* is used to signify that we can conceptually 'cast' sample subjects into participant or nonparticipant roles or 'types' even if the sub-sample from which they are drawn does not include people who made participation decisions during the test period for the program. For example, in the current setting we are considering the decisions of people who bought new homes during the program period. Clearly this population can be divided into people who bought participating homes and those who bought nonparticipating homes, and we can use this information along with other supporting data to estimate a probability function that can be used to calculate P'_R. Once this function is calculated, however, we can make use of it to estimate P'_R for people living in homes constructed in the absence of the program. *For the pre-program buildings* P'_R *is an estimate of the probability that the building contractor would have participated if the building had been constructed during the program period.*

What types of factors affect this participation probability? Classifying buildings in terms of their location (weather structure) and other characteristics (single-family/multi-family, etc.), we can imagine that the likelihood of builder participation varies with the type of building/location under construction. I will discuss this issue in more detail below. As noted above, however, an economic argument suggests that the types of buildings/locations with the highest builder participation rates would be those that would gain the most energy savings from conservation. This means that we would expect greater builder participation rates for larger buildings in areas with more extreme weather and with relatively stable populations of future energy bill payers. In the analysis below we propose a method for estimating these participation probabilities.

Leaving aside, for the moment, how this participation probability estimate will be obtained for buildings constructed before the program started, we can write a general form as follows for a conditional demand equation that describes consumption for buildings constructed before the program.[2]

$$\begin{aligned} e_{pre} = {} & e'_{Npre}\ [P'_N] \\ & + e'_{Rpre}[P'_R] + u_{pre} \end{aligned} \tag{2}$$

where e_{Pre} is observed consumption in buildings built before the program was started, e'_{NPre}, is estimated consumption for nonparticipating-type buildings constructed before the program was started, e'_{RPre} is estimated consumption in participating-type buildings constructed before the program was started, and u_{Pre} is a disturbance term.

In the actual regression equation the estimated consumption for these two groups will be broken down by end-use as is customary in conditional demand estimation. This means that each of these e' variables (e'_{Npre} and e'_{Rpre}) actually represent complete conditional demand equations.[3] A conditional demand structure is recommended here so that consumption can be modeled in separate end-use categories in these segment equations. This is a useful approach since it allows the important interactions among program variables and building and environmental characteristics to be taken into account.

Furthermore, the conditional demand equations for e'_{NPre} and e'_{RPre} can be used to test for the effects of factors related to the construction year of the building. This aspect of the analysis is useful since it allows us to account for improvements in building standards, as well as other market- and technology-driven improvements in building materials and practices over time. In addition, this aspect of the analysis allows the equations to be used for estimating (end-use and total) energy consumption depending on the year of construction. This means that although these equations are calculated from data that were generated on buildings constructed in the absence of the program, *the parameters of the* e_{Pre} *equation can be used to project an estimate of consumption during the program period.* In the analysis below I use projections of consumption based on the parameters of the e'_{Npre} and e'_{Rpre} equations to compute what consumption would have been during the program period, if there had been no program.[4]

Note that, since $P'_N = 1 - P'_R$:

$$e_{pre} = e'_{Npre}\,[1-P'_R] + e'_{Rpre}[P'_R] + u_{pre} \tag{3}$$

or,

$$e_{pre} = e'_{Npre} + (e'_{Rpre}-e'_{Npre})[P'_R] + u_{pre} \tag{4}$$

In this latter form, the standard errors and coefficients associated with the estimated term multiplying P'_R could be used to test directly whether e'_{Rpre} differs from e'_{Npre}. If the coefficients of e'_{Rpre} and e'_{Npre} are not significantly different from each other, the estimating equation can be simplified as follows:

$$e_{pre} = e'_{pre} + u_{pre} \tag{5}$$

In this latter equation, the consumption in the absence of the program is modeled the same way for the nonparticipant and participant buildings.

For buildings constructed after the program began, we can estimate a conditional demand equation as follows:

$$e_{post} = e'_{Npost}\,[D_N] + e'_{Rpost}[D_R] + u_{post} \tag{6}$$

where the subscript 'post' indicates a building constructed during the program period, D_N is a 0,1 dummy variable that is 1 if the building contractor *did not* participate and D_R is a 0,1 dummy variable that is 1 if the builder *did* participate.

We can estimate both equations (for buildings constructed before and after the program began) in one regression as follows:

$$\begin{aligned} e = {} & e'_{Npre}\,[P'_N]\,Dpre \\ & + e'_{Rpre}\,[P'_R]\,Dpre \\ & + e'_{Npost}\,[D_N]\,Dpost \\ & + e'_{Rpost}\,[D_R]\,Dpost + u \end{aligned} \tag{7}$$

where Dpre is a 0,1 dummy variable that is 1 for buildings constructed *before* the program began and Dpost is a 0,1 dummy variable that is 1 for buildings constructed *after* the program began, and u is an overall error term. The error structure of this equation may make it desirable to use GLS estimation techniques for this regression. In addition, it may be argued that the dummy variables D_N and D_R are correlated with u (a simultaneity or self-selection bias argument). In this case, it would be appropriate to replace these dummy variables with the instruments P'_N and P'_R (estimated using exogenous variables).

Equation (7) is the *type-casting* paradigm for estimating equations that can be used to measure the impact of efficient new-construction programs.

Calculating Net Savings

The net savings for the program would be computed from this estimation procedure using the following preliminary calculations:

1. Estimate the average energy use for occupants of participant buildings after the new-construction program *has been implemented,* $ebar_{Rpost}$, by evaluating the e'_{Rpost} equation using the input values (on floor space, weather, etc.) taken from the program participants.

2. Estimate the average energy use for occupants of participant buildings if the program *had never been implemented,* $ebar_{RPre}$, by evaluating the e'_{RPre} equation using the input values taken from program participants.

3. Estimate the average energy use for occupants of nonparticipant buildings after the new-construction program *has been implemented,* $ebar_{Npost}$, by evaluating the e'_{Npost} equation using the input values taken from the program nonparticipants.

4. Estimate the average energy use for occupants of nonparticipant buildings if the program *had never been implemented,* $ebar_{NP,e}$, by evaluating the e'_{Npre} equation using the input values taken from the program nonparticipants.

It should be stressed that the designation 'pre' simply means that the relevant average consumption was computed using the parameters of the relevant pre-prograrn equation evaluated to calculate consumption for the year in which the program began. All of the input values (floor space, etc.) are taken from the occupants of participant and nonparticipant buildings constructed during the program period. The input values are taken from the program period in order to hold the building amenities at the program year levels.

Using these calculations of average consumption, we would compute the total net program savings, s, as the sum of 1. the free-driver/spillover savings and 2. the net savings for the participants as follows:

$$s = (ebar_{Npre} - ebar_{Npost})\ N + (ebar_{Rpre} - ebar_{Rpost})\ N \tag{8}$$

In this equation, the average differences $[(ebar_{NPre} - ebar_{Npost})$ and $(ebar_{Rpre} - ebar_{Rpost})]$ are multiplied by the total number of customers in each category (N and R, for nonparticipants and participants, respectively) to obtain *total* net savings.

Note that $(ebar_{Npre} - ebar_{Npost})N$ is the total difference in energy consumption *for nonparticipants* that is associated with the implementation of the program. This is the estimate of the total free-driver/spillover effect for nonparticipants. In the same way, $(e_{RPost} - e_{Rpre})R$ is the total difference in energy consumption *for participants* that is associated with the implementation of the program.

This participant difference term can be shown to be the estimate of the participant savings net of the free-rider effect as follows. First, note that even though we do not specifically identify the free riders, we can represent average participant consumption in the post period, $ebar_{Rpost}$, using the weighted average equation:

$$ebar_{Rpost} = ebar_{RPpost}\ (RP/R) + ebar_{RFpost}\ (RF/R) \tag{9}$$

where, $ebar_{RPpost}$ represents average consumption during the program period for the participants that are affected by the program, $ebar_{RFpost}$ represents average consumption during the program period for the free-rider participants, RP represents the number of customers in participant buildings that were affected (made more efficient) by the program, and RF represents the number of customers in free-rider participant buildings that (by definition) were not made more efficient by the program. Multiplying this last equation by R, we have:

$$ebar_{Rpost}\ (R) = ebar_{RPpost}\ (RP) + ebar_{RFpost}\ (RF) \tag{10}$$

This equation is an estimate of the total consumption in participant-type buildings constructed during the program period. Using a similar approach, we can write the total participant consumption in the absence of the program as follows:

$$ebar_{Rpre}\ (R) = ebar_{RPpre}\ (RP) + ebar_{RFpre}\ (RF) \tag{11}$$

where $ebar_{RPpre}$ represents average consumption, computed from the non-program period equation (e'_{RPre}), for the participants that are affected by the program, $ebar_{RFpre}$ represents average consumption during the non-program period for the free-rider participants, and the remaining variables are defined as above.

Now, considering only the direct efficiency effects and the definition of a free rider,[5] it is clear that $ebar_{RFpost} = ebar_{RFpre}$. Thus, we would calculate the total difference m participant consumption, attributable to the program, as follows:

$$(ebar_{Rpost} - ebar_{Rpre})\ R = (ebar_{RPpost})\ RP - (ebar_{RPpre})\ RP \qquad (12)$$

This means that $(ebar_{Rpost} - ebar_{Rprc})R$, the total difference in participant consumption attributable to the program, arises solely from the consumption difference in buildings affected by the program, as we would expect. *This participant impact estimate, therefore, does not depend upon (i.e., is net of) the free-rider buildings.*

It may be useful to note that a similar chain of reasoning can be used to establish that the free-driver/spillover savings can be logically computed as follows:

$$(ebar_{Npost} - ebar_{Npre})\ N = (ebar_{NPost})\ NP - (ebar_{Npre})\ NP \qquad (13)$$

where, $ebar_{NPpost}$ represents average consumption during the program period for the nonparticipants that are affected by the program (the free-drivers), $ebar_{NPpre}$ represents average consumption during the non-program period for the free-driver nonparticipants, NP represents the number of customers in nonparticipant buildings that were affected (made more efficient) by the program, and the other variables are defined as above.

Type Casting Analysis: Empirical Results

In this section we present the initial estimates obtained from our *type casting analysis.* To keep the issues simple, we limited ourselves to relatively simple equations focusing upon air-conditioning usage. The regression data set was constructed from two major components that were sampled from Southern California residences: a subsample of buildings erected prior to the onset of a utility-sponsored rebate program for newly constructed residences; and, a subsample of buildings erected during the rebate program period (1990 and later).

We limited the sample to single-family houses built since 1978, and for each house, a maximum of two years of consumption data were analyzed. The total number of time-series/cross-section observations for the regression was 12,320.

The probabilities of program participation were estimated from ZIP code participation rates alone. Using this approach we were not able to detect any preprogram difference in air-conditioning consumption associated with the participation probability variables. For the houses built after the program began, however, we were able to detect a difference in air conditioning usage associated with program participation.

Energy consumption (kWh Per Month) in this equation is modeled as the sum of the air-conditioning and other unspecified energy use. The unspecified use is modeled as a simple function of the number of people (Occupants) in the residence. The air-conditioning portion of the load is modeled as a simple function of an engineering prior estimate of air-conditioning use (Aceng), and a set of interaction variables including a year-of-construction trend (ConYear) and the program participation dummy (0, 1) variables (Participant, Nonparticipant). The air-conditioning use estimate is zero for homes in which the appliance is not present. This, of course, is equivalent to the usual conditional demand practice of multiplying appropriate sets of variables by 0,1 dummy appliance indicator variables. The Participant and Nonparticipant variables can only have the value one during the time that the program was active. Homes built before the program began are classified as neither participants nor nonparticipants. These participation variables were replaced in this equation by their conditional mean values from a frequencies procedure in which the subjects were broken into cells defined by categories of house size, average July cooling degree-days, and the average years of tenancy in the zip code (see the discussion preceding equation 2). The categories for each of these three variables were defined by dividing the range by 10. No weighting was used to account for the different cell sizes. This method for estimating these participation probabilities is somewhat crude and the results would probably benefit from a maximum likelihood LOGIT or PROBIT estimate of the probability function. The overall adjusted R^2 for the usage equation is .59 and the estimated parameter for the equation are as follows (t-ratios in parentheses). (See Table 1.)

In this equation, the value of the trend term (ConYear-1990) is zero for homes built in the beginning of the program time frame. This trend term is used to model the adjustment of the air-conditioning load over time in the absence of the program. The Aceng coefficient (.8861) indicates that the estimate of energy consumption in 1990 *in the absence of the program* would be 88% of the engineering model prediction (ACeng). Thus, the point estimate of -.1152 for the participant coefficient suggests that participant loads are roughly (.12)*(ACeng) less than would have been expected in the absence of the program. The point estimate of -.03 for the nonparticipant coefficient suggests that nonparticipant loads are (.03) *(ACeng) less than would have been expected in the absence of the program (the spillover effect). The current simple

Table 1. Dependent Variable: kWh per Month

Independent Variable	Coefficient	t-Ratio
Intercept	632.7125	34.8
Occupants	71.3178	23.1
ACeng	.8841	18.3
ACeng (ConYear-1990)	-.0002	-6.7
ACeng (Participant)	-.1152	-3.9
ACeng (Nonparticipant)	-.0543	-2.5

specification of the model is sufficient to demonstrate the use of the proposed method. In general, however, we would expect the results of this analysis to improve with a more detailed specification of the end-use details.

Conclusions and Alternatives

The *type-casting* method proposed in this paper is designed to measure the net savings associated with a new building construction program in the sense that it is designed to measure participant savings net of free-rider effects as well as the free-driver/spillover impact of the program on nonparticipants.

Several cautions are in order. Although the paper deals with several important aspect of net savings measurement, we do not address two of the important net/gross issues (persistence and rebound effects) here since we are preparing a separate paper dealing with them. Furthermore, although we use the comparison concepts of pre and post in this paper, the same essential work could be carried out using geographic regions with and without the program as an equivalent comparison framework. Of course, suitable variables would have to have to be available to control for nonprogram differences between (among) the regions.

The next step in the modeling process would be to estimate the participation probabilities using maximum likelihood LOGIT or PROBIT techniques. This might give us more insight into the pattern of air-conditioning consumption in both the pre- and post-periods. To model these participation probabilities we would concentrate on the role of the rebate program in affecting the potential profits of builders. The probability that a builder would participate, and would have important and marketable gains from conservation, depends to a large extent on the character of the building (large, small, etc.), the climate zone (very cold, very hot or not), and the character of the potential occupants (would they regard efficiency as a selling point?). For example, even a large building in the desert might not be much more highly valued for a more efficient air-conditioner if the targeted occupant market tended to move often; or their discount rate tended to favor current consumption abnormally; or they didn't have the sort of education that allowed them to understand the linkage between energy conservation and expenditures, or to value conservation apart from this linkage.

Further, the overall R^2 would probably be improved by a more detailed modeling effort (more end-uses). The individual t-ratios might also be improved by a more detailed model.

Data sets suitable for carrying out the *type-casting* scheme should include survey, billing, conservation program information, and weather data sets for buildings constructed during the program period by both participant and nonparticipant builders. In addition, a corresponding preprogram (program-unavailable) data set containing survey, billing and weather data sets should be used to aid in estimating what consumption would have been in the absence of the program. Apart from these basic data sets, some end-use metering might be justified to increase the accuracy of the savings estimates; and some pre-move data (billing, survey and weather) for the new construction occupants might be interesting since it would give us more direct pre-post information than would otherwise be available.

There are, of course, many other methods that could be used to estimate the impacts of an energy efficient new-building construction program. For example, it is possible to attempt to identify potential free-riders and free-drivers from survey data using self-reported data. This type of information can be quite useful but some sort of statistical/econometric procedure should be used to check on the reliability of the self-report. In addition, discrete choice analysis can be used to distinguish among the market segments of interest (free-rider participants, participants affected by the program, nonparticipant free-drivers, etc.). This approach can be very demanding in terms of data requirements and analytical detail. It can, however, be combined with an energy usage equation to yield defensible program savings estimates.

By contrast, the *type-casting* method does not require any self-reported assessment of free-ridership, etc.; and it does not require the estimation of a long sequence of discrete choice equations. Rather, *type-casting is* based upon revealed behavior data on the actions of builders and occupants; has relatively modest data and analytical requirements (a slightly modified conditional demand equation), though it can make use of very detailed data sets and analyses; allows us to make profitable use of existing data sets; and yields group estimates of expected energy consumption that can be used to compute program impacts that account for net participant and free-driver effects.

A final question (which I won't answer here), might be raised about whether this approach would be applicable to other program measurement applications, such as rebates for efficient replacement equipment. Why would we want to do such a thing? The advantage would be that the type-*casting* method, at its heart, is a technique for obtaining meaningful base-case comparison groups. It allows us to make use of data generated in the absence of the program to compute an estimate of what consumption would have been in the absence of the program for the market segments of interest; in this case, participants and nonparticipants. This base-case information can be combined with conventionally generated estimates (e. g., conditional demand analysis) of the market segment consumption during the program period to compute the impact of the program on each observable market segment.

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Endnotes

1. This breakdown into two categories is for convenience in explaining the ideas rather than any limitation of the method. What is important is that the membership in the various groups be observable, at some point. For example, it might be interesting to extend the analysis to three market segments by considering two kinds of nonparticipants: those that installed efficient equipment and those that did not. The main requirement for this is that we would have to observe at least some nonparticipants that chose to install efficient equipment and nonparticipants that chose to install inefficient equipment.

2. Pooled cross-section/time-series data sets are used to estimate the equations discussed in this paper. Thus the variables are expected to vary over buildings (i.e., utility customers) and time. Since the subscripts I use in this paper are already somewhat adventurous, I have not used time and customer subscripts explicitly though they should be understood as applying.

3. This means that we would estimate an equation for e'_{Npre} in typical conditional demand form as follows:

$$e'_{Npre} = e_{1,Npre}\,(d'_{1,Npre}) + \ldots + e_{n,Npre}\,(d'_{n,Npre})$$

   where n is the number of appliance categories investigated in the study, $e'_{i,NPre}$ represents energy consumption in the i'th end-use category (i= 1,. .n), and $d'_{i,NPre}$ is a dummy variable indicating whether end-use i is present (more precisely, whether it is connected to the meter). A conditional demand equation for e'_{Rpre} can be written in a similar manner.

4. A short clarifying note to the econometricians: This dependence of consumption on the age of the building can be viewed as a type of trend-related term. It is different, however, from the usual trend-related term that rises or falls with successive observations on the dependent variable. In fact, for a given building (cross-section observation), this age term is constant, not time-varying. This means that, for the equations to be modeled, it would be quite possible to have two different types of trend-related effects: one varying over the time-period of sampled consumption for each customer; and another varying, independently of the first, over the buildings in the sample.

5. In this case a free-rider is a participant builder who would have built the same house if the program had not existed. This sentence simply says that if the building is the same and the occupants are the same, then consumption will be the same (with and without the program).

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