Theory-Based Estimation of Energy Savings from DSM, Spillover, and Market Transformation Programs Using Survey and Billing Data

*Adrienne Vayssières Kandel, California Energy Commission**

ABSTRACT

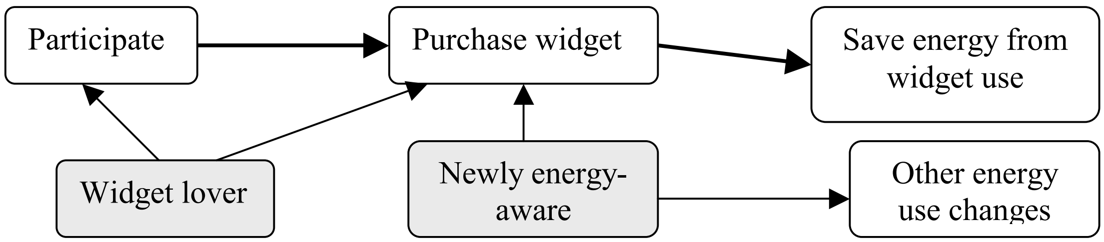
Energy policy makers have begun to turn away from market transformation programs because they have no way to estimate their load impacts. Demand-side management programs should aim for maximum nonparticipant spillover, but there has been no way to estimate their success in saving kWh that way. This paper proposes a regression-based method to estimate the load impacts of energy efficiency and market transformation programs, including their spillover, using survey and billing data on people affected and unaffected by the program. It does this by extending the instrumented decomposition technique to encompass spillover and market transformation effects based on testable theories. The theoretician develops a program causality diagram and decomposes savings into components, which are then consistently estimated. A first regression stage estimates relationships between variables such as program participation, indirect exposure to program effects, and/or technology purchases, depending on the program and theory. A second stage estimates program-induced savings, including spillover where applicable, and other savings components such as free rider savings and program-unrelated savings. Examples covered include: rebate programs, pure publicity programs, and a contractor certification program.

General Approach

Presumably, program designers have a theory about how their program will save energy. Figure 1 shows that theory for a simple widget rebate program without spillover. The heavy arrows indicate intended program effects: rebates should cause purchases, which should cause savings. Normal arrows identify other causal pathways to watch out for in modeling: unobserved factors (shown in gray) and unrelated energy use changes, which make program effects difficult to discern in simple regression comparisons of participants and nonparticipants. You may think a widget purchaser was motivated by participation, when in fact she was simultaneously motivated to purchase and to participate based on her deep love of widgets. Similarly, the decisions to purchase the widget and to make other energy use changes can be simultaneous, based on new energy awareness.

The instrumented decomposition technique explained in this paper will allow statistically consistent estimates of program-induced energy savings in the presence of this simultaneity, based on the testable theory you develop about program effects. In a first stage, program theory translates into an often discrete choice estimate of program effects on technology or practices, like extant methods for estimating free ridership and spillover rates. In a second stage, those effects are correctly included in a savings regression, whereas multiplying net savings ratios by separate billing-based savings estimate causes bias and inconsistency (Kandel 1999a,b). For full implementation, the method requires survey data and pre- and post-program billing data for samples of participants and nonparticipants (or households that indirectly exposed to the program and households that are not), and must concern a technology that has a measurable impact on adopters' electric bills. I present the method by providing examples of its applications.

Figure 1. Widget Rebate Program



Example 1: Evaporative Cooling (EC) Rebate Program—No Spillover

In 1994 Southern California Edison conducted an evaporative cooler rebate program, and matched pre- and post-program energy bills with residential surveys sent to a sample of participants and nonparticipants. When I tested the instrumented decomposition procedure described below on this rebate program, the method turned out to be surprisingly precise. With free ridership and self-selection effects properly disentangled, the net savings estimate of 3 kWh/day per participant was robust to changes in independent variables, and had a low standard error of only 12% of the net savings estimate (Kandel, 1999a,b). (Standard error is calculated using Newey's moments method.) This analysis did not include spillover, as no particular spillover theory informed questionnaire development. Here is the procedure:

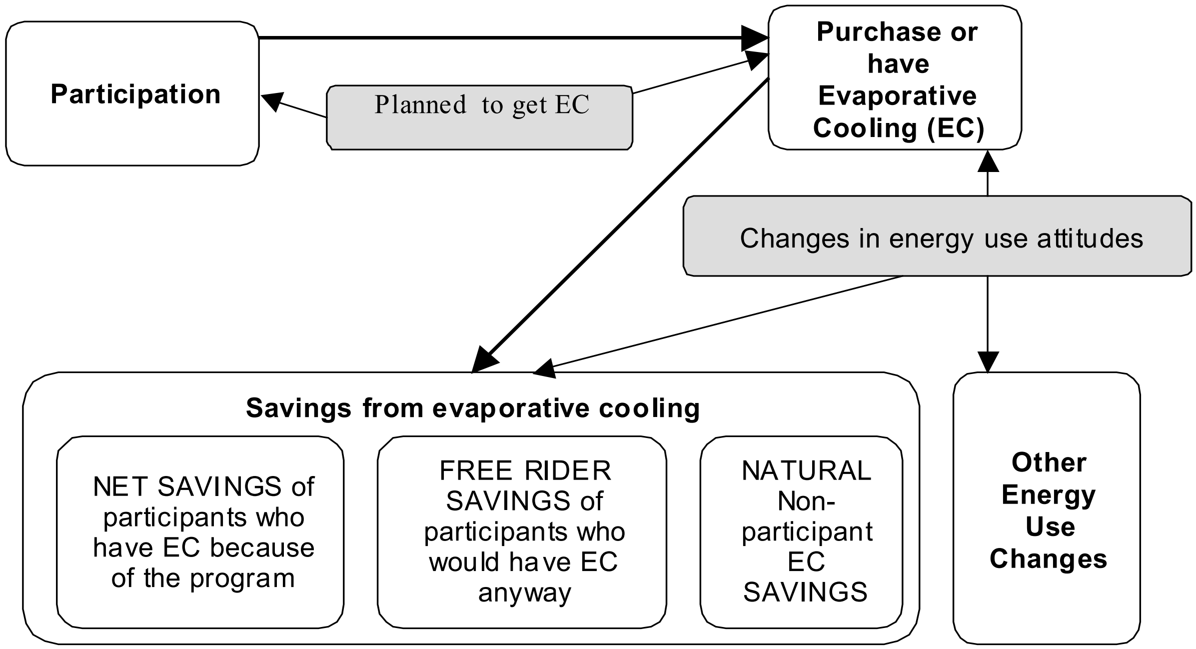
I. Theorize: Make a Program Causality and Savings Decomposition Diagram

In the program causality and savings decomposition diagram (Figure 2)

- Intended program effects are: participation → evaporative cooling → savings.
- Gray boxes show unobserved factors that influence at least 2 decisions, requiring those decisions to be treated as simultaneous. You cannot assume that participation causes EC purchase because plans to buy can cause them both. Similarly, EC purchasers' savings may come from the purchase, or from a change in attitudes that motivated the purchase.
- Savings is decomposed into savings from evaporative cooling and other energy use changes. The "Savings from evaporative cooling" box includes net savings – the figure we seek – as well as free rider savings and savings from nonparticipants naturally acquiring evaporative cooling.
- To avoid clutter, diagrams in this paper exclude observed, exogenous variables.

This causality and decomposition diagram will govern an instrumental variables estimation procedure. First, households will be classified in according to whether they should have savings from evaporative cooling, and of what type (step II). Then savings will be simultaneously estimated for each type of household (step III), so that net savings can be separated out and summed over all households (step IV).

Figure 2. Program Causality and Savings Decomposition for Evaporative Cooler Rebate Program



II. Discrete Choice Regression: Estimate Choices such as Participation and Purchase

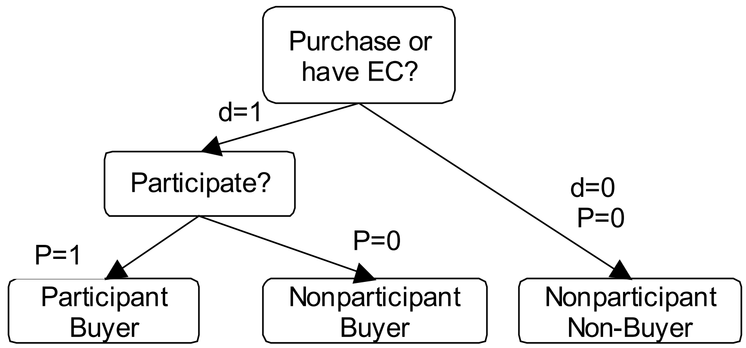
In this program, all participants must buy EC, so there are 3 possible outcomes: participant buyer, nonparticipant buyer, nonparticipant non-buyer. Since these participation and purchase decisions are simultaneous, the easiest way to estimate them is using a nested logit model (Train et al, 1994). Figure 3 shows the nested logit tree (which illustrates error correlation, not causality). It's best to estimate the nested logit simultaneously rather than sequentially, and if you've oversampled participants you'll need to use a sample stratification correction. I found weighting each observation horrendously inefficient and only got good variances when I applied the Manski-McFadden (1981) conditional maximum likelihood estimator. Imbens (1992) offers a lower variance true MLE – with today's faster computers it may work easily.

Estimation yields equations for the probability of participation (*P*) and of having the studied "device" (*d*), based on observed variables such as location, climate, type of home, income, remodeling events, and initial energy use. To distinguish between free rider and net savings, we also have to estimate the probability of buying the device without participating, the "natural propensity to buy" (*b*)." For free riders, *b*=1. Applying Bayes' Law:

$$\Pr\left(b_i = 1\right) = \Pr\left(d_i = 1 \mid P_i = 0\right) = \frac{\Pr\left(d_i = 1 \; and \; P_i = 0\right)}{\Pr\left(P_i = 0\right)} \tag{1}$$

Estimated natural propensity to buy, $\hat{b}$, is the estimated probability of buying and not participating (middle leaf on the nested logit tree) divided by the estimated total probability of not participating (sum of the middle and right leaves).

Figure 3. Nested Logit Estimation Tree



III. Savings Regression: Linearly Estimate Components of Savings

Let "savings" mean energy use after the program minus energy use before. Define "device savings" as savings caused by the program-targeted device – evaporative cooling in this case – , and define "unrelated savings" as other energy use decreases that year. Positive, negative, or zero unrelated savings enter into everyone's energy bill. The 3 device savings categories, on the other hand, are only nonzero for households falling into their evaporative cooling buyer type: nonparticipant buyers (where P=0, b=1, d=1), free riders (P=1, b=1, d=1), and the participant program-induced buyers responsible for net savings (P=1, b=0, d=1).

Each type of savings depends partly on variables that can be controlled for in a linear regression: building envelope and cooling practices, for example, affect device savings; changes in appliance stock or occupancy affect unrelated savings; weather, economics, and demographics can affect both types of savings. These variables drive a linear regression that uses P and b interaction terms to distinguish device savings types, and non-interacted variables driving unrelated savings. (The variable d turns out to be redundant since all device buyers have nonzero P or b). In equation (2), each subscripted X represents the set of independent variables affecting a savings component, including component-specific intercepts.

$$\underbrace{s_i}_{\substack{\text{total}\\\text{savings}}} = \underbrace{\beta_u' X_{ui}}_{\substack{\text{unrelated}\\\text{savings}}} + \underbrace{(1-P_i)\hat{b}_i(\beta_n' X_{ni})}_{\substack{\text{nonparticipant buyer}\\\text{device savings}}} + \underbrace{P_i\hat{b}_i(\beta_f' X_{fi})}_{\substack{\text{free rider}\\\text{device savings}}} + \underbrace{P_i(1-\hat{b}_i)(\beta_s' X_{si})}_{\text{net savings}} + \varepsilon_i \qquad (2)$$

b is replaced by $\hat{b}$, used as an instrumental variable. Instrumenting b will handle potential self-selection in the form of EC purchasers' simultaneous propensities to save energy and to naturally buy EC.

Where categories of device savings share X variables, you can avert multicollinearity problems by restricting their coefficients to be the same if it makes sense behaviorally. In Kandel (1999a,b) the participant and nonparticipant data involved different purchase time periods, making nonparticipant buyers very different from participant buyers. But free riders and program-induced participants were similar enough for me to treat their differences as an average effect, through separate intercepts. The equation estimated was therefore:

$$\underbrace{s_i}_{\substack{\text{total}\\\text{savings}}} = \underbrace{\beta_u{}' X_{ui}}_{\substack{\text{unrelated}\\\text{savings}}} + \underbrace{(1-P_i)\hat{b}_i\beta_n{}' X_{ni}}_{\substack{\text{nonparticipant buyer/owner}\\\text{device savings}}} + \underbrace{P_i\hat{b}_i\alpha_f + P_i(1-\hat{b}_i)\alpha_s + P_i\beta_p{}' X_{pi}}_{\text{participant device savings}} + \varepsilon_i \qquad (3)$$

α_f and α_s are the free rider and net saver intercepts; X_p no longer includes an intercept.

The regressions in equations (2) and (3) are consistent, so long as you avoid taking a variable that influences two types of savings and only use it in explaining one type, which would then pick up effects of the excluded copy's savings type (Kandel, 1999a).

If participation and savings decisions are simultaneous after controlling for observed factors including the purchase decision, then consistency requires that P be replaced with $\hat{P}$. If participants form much less than 10% of the population, however, $\hat{P}$ will vary too little to be a good instrument, and you should keep P, trading a little bias for much lower variance.

IV. Sum Predictions

Net savings is the weighted sum over participants of their individual regression-predicted net savings values. Letting weight w_i =[population size in household i's stratum]/[sample size in household i's stratum], net savings is $\sum_i w_i P_i (1-\hat{b}_i)\hat{\beta}_s{}' X_{si}$ if equation (2) was used, or $\sum_i w_i P_i (1-\hat{b}_i)(\alpha_s + \beta_{pi}{}' X_p)$ under equation (3).

Example 2: Evaporative Cooling Rebate Program with Spillover

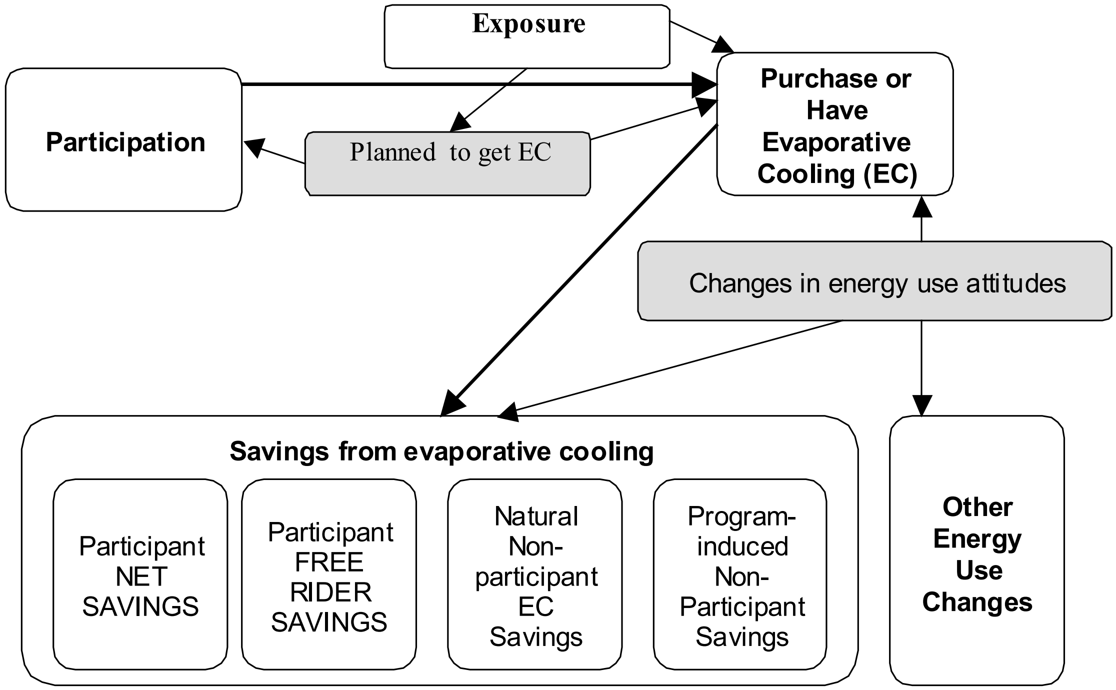
The basic changes here are that there is a new category of EC savers – program-induced nonparticipant buyers, and that there is a new input to the EC purchase decision – exposure to something the rebate program affects. Exposure will be based on a theory of market effects (discussed later in this section); a simple example is seeing evaporative cooling on a neighbor's home. Here's how theory-based instrumental decomposition works in this example:

I. Theorize

The new causality and decomposition diagram, Figure 4, looks like the old one except:

- A new "Exposure" event affects but is not affected by the household's purchase and participation decisions. (Not depicted: one household's purchase may expose another.)
- A new "Savings from evaporative cooling" category includes a measure of nonparticipant spillover.

Figure 4. Program Causality and Decomposition Diagram with Spillover



II. Discrete Choice Regression

Participation and purchase can still be estimated in a nested logit regression; the change is that one of the independent variables will be Exposure. If exposure turns out to have no meaningful effect on purchase, then our theory of spillover is not supported, and we return to a no-spillover estimation, as in Example 1. If exposure does prove to influence purchase, however, then we will estimate program impacts as participant net savings plus exposure-caused nonparticipant spillover. We use our nested logit regressions to estimate *b*, the natural propensity to buy, as follows:

- For a nonparticipant buyer, b_i is the probability he would have bought evaporative cooling without the exposure caused by the program. That is $b_i = Pr(d_i=1|E_i=E_0)$, where E_0 is the no-program level of exposure. To estimate b_i we apply the estimated regression equation for $Pr(d_i=1)$ to individual *i*, with *E* reset from its observed value to E_0 (Seiden and Platis, 1999). Nonparticipant spillover becomes the savings of program-induced nonparticipant buyers, nonparticipants with d_i=1, but b_i=0.
- For a participant, b_i is the probability she would have bought evaporative cooling without the program and without the exposure caused by the program:

$$\Pr\left(b_i = 1\right) = \Pr\left(d_i = 1 \mid P_i = 0, E_i = E_0\right) = \frac{\Pr\left((d_i = 1 \text{ and } P_i = 0) \mid E_i = E_0\right)}{\Pr\left(P_i = 0 \mid E_i = E_0\right)} \qquad (4)$$

Note that $\hat{b}$ is again the ratio of the middle nested logit leaf over the two right leaves in Figure 3. In this case, however, $\hat{b}$, $\hat{P}$ and $\hat{d}$ are obtained by replacing each E_i with E_0 when you apply the already-estimated regression coefficients.

III. Savings Regression

Now savings has five components instead of four, because nonparticipant buyer EC savings is split into program-induced and naturally occurring parts. A regression equation with full decomposition and no restrictions would be:

$$s_i = \underbrace{\beta_u{}' X_{ui}}_{\substack{\text{unrelated}\\ \text{savings}}} + \underbrace{(1-P_i)d_i\hat{b}_i\beta_a{}' X_{ai}}_{\substack{\text{nonparticipant buyer}\\ \text{natural device savings}}} + \underbrace{(1-P_i)d_i(1-\hat{b}_i)\beta_c{}' X_{ci}}_{\substack{\text{nonparticipant buyer}\\ \text{program-induced device savings}}} + \underbrace{P_i\hat{b}_i\beta_f{}' X_{fi}}_{\substack{\text{free rider}\\ \text{device savings}}} + \underbrace{P_i(1-\hat{b}_i)\beta_s{}' X_{si}}_{\substack{\text{participant program-}\\ \text{induced savings}}} + \varepsilon_i \tag{5}$$

Nonparticipant device savings now has two components – naturally occurring and program-inspired. The variable d is no longer redundant, and must be included in nonparticipant buyer interaction terms. Consistency does not require that d be replaced with by an instrument, $\hat{d}$, unless there are unobserved factors influencing whether a person will purchase after being exposed. (The instrument $\hat{b}$ controls for unobserved factors influencing whether a person would purchase without exposure.)

To limit multicollinearity, natural and program-induced nonparticipant buyers can share device savings variables and coefficients, with separate intercepts covering the difference between the two groups:

$$\begin{aligned} s_i = \beta_u{}' X_u &+ \underbrace{(1-P_i)d_i\hat{b}_i\alpha_a + (1-P_i)d_i(1-\hat{b}_i)\alpha_c + (1-P_i)d_i\beta_n{}' X_n}_{\text{nonparticipant buyer device savings}} \\ &+ \underbrace{P_i\hat{b}_i\alpha_f + P_i(1-\hat{b}_i)\alpha_s + P_i\beta_p{}' X_p}_{\text{participant device savings}} + \varepsilon_i \end{aligned} \tag{6}$$

IV. Sum Predictions

Net program effects would be the sum of program-induced nonparticipant EC savings (nonparticipant spillover) and program-induced participant savings. Based on regression equation (6), that's

$$program\ load\ impact = \sum_i w_i(1-\hat{b}_i)\Big((1-P)_i d_i(\hat{\alpha}_c + \hat{\beta}_n{}' X_{ni}) + P(\hat{\alpha}_s + \hat{\beta}_p{}' X_{pi})\Big) \tag{7}$$

Now, here are 3 theories of spillover from this program, and how to test and apply them:

Theory 1a: lessened social class stigma causes market change. The SCE program marketed evaporative cooling as a supplement to air conditioning, and had considerable success with well-to-do homeowners, suggesting it was reducing the social barrier to adoption created by the low class "swamp cooler" image. One might hope that people seeing the EC's on "nice" homes might lose their own prejudices against it, and that the program could cause a permanent change in norms, hence market transformation. A social scientist could refute or refine that theory by conducting some residential interviews.

Suppose the interviews support the theory, which now needs to be tested on a representative sample. Based on the refined theory, the social scientist develops a question or set of questions, or conjoint analysis-supporting set of pictures of homes with and without

EC to rate. This question set will be included in the residential survey sent to program participants and nonparticipant comparison group, while their energy use changes are observed. From responses, the researcher will code a variable such as "Attitude: views EC as slummy." In addition, the researcher develops questions leading to the variable "Exposure: has seen or heard about EC on classy homes."

The program theory is that program raises E, exposure, which lowers A, attitude, thereby increasing purchases, d.

Testing the theory. To test the theory that the program raises E the researcher will need to sample pre-program, or sample people from a comparable place without the program, and establish a no-program level of E, possibly individualized to each household as a function of demographic variables. Alternatively, the researcher may know that E=0 in the absence of the program, if virtually no classy homes have *EC* at the start.

To test the theory that increased *E*xposure lowers *A*ttitude, the researcher regresses A on E and other relevant variables (demographic and geographic) using the survey sample. Demographic and geographic variables should control for a pre-disposition to attitude affecting exposure. If not, use a simultaneous estimation method (see discussion later in Example 3, the widget promotion subsection). To test the theory that *A*ttitude affects Purchases, regress purchases, d, on Attitude, A, for people who don't already have EC. If these theories prove correct, you can estimate load impacts.

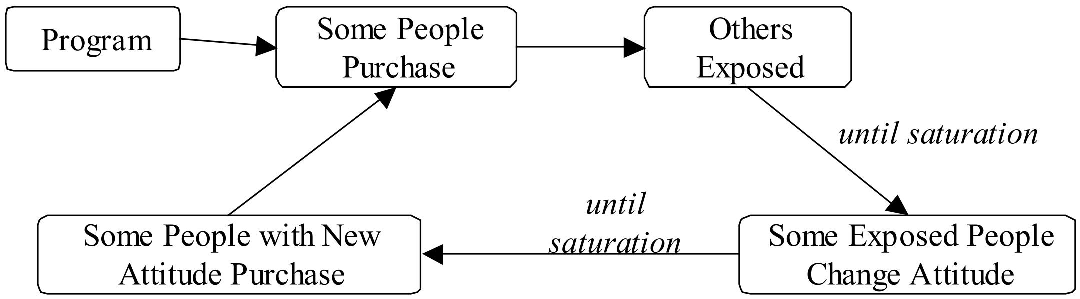
Load impacts. Use E, exposure, in the estimation of net savings with spillover described above – a nested logit regression followed by a savings regression like equation (6). Drop A as an unnecessary intermediate variable between E and purchase choices. Or to evaluate only the effects of the change in attitude (ignoring unproven effects like learning about EC) use A instead of E. (It's best to estimate no-program A_0 directly on your no- or pre-program sample. If that's not possible, estimate A_0 as predicted attitude when E is set to E_o).

Theory 1b: lessened social class stigma causes sustainable market transformation. To what extent is the market transformed, with what load impacts? A theory of market transformation is that the program leads to purchases, which lead to exposure, which improves attitude and leads to more purchases, which lead to more exposure, and better attitude. Market demand increases via a permanent change in consumers' preferences. At some saturation point, more exposure will not affect attitude, and at another saturation point, attitude will no longer affect preferences and therefore purchases (they will be limited by other considerations than a low-class perception). This is shown in Figure 5.

To test this theory after the program has ended, the researcher can conduct surveys once a year to ask respondents about their exposure, attitude, and purchase. Running the same discrete choice regressions as before, he can see whether and how much E continues to affect A, and whether and how much A continues to affect purchases.

If the annual surveys include billing data, the researcher can run a full instrumented decomposition model to estimate net savings today due to a program n years ago. Energy changes are over the n-year period. Purchase, d, participation, P, and exposure, E, are measured over the n-year period as well (as whether they occurred over that period, or not).

Figure 5. Market Transformation Theory Diagram



If annual surveys don't include billing data, the researcher can estimate the n^{th} period's load impact of market transformation as follows. Remember all subjects are nonparticipants who had not purchased EC before period *n*.

1. Estimate the effect of *E*xposure on *d*, purchases of EC during period *n*, in a binary choice regression such as $\Pr(d=1) = F(X\beta + \alpha E)$. Now calculate for each subject the predicted probability of purchase with E_i set at their expected pre-program level, E_0. Alternatively, use *A* in the regression and A_0 in simulation if you only want to consider spillover through exposure's effect on attitude, for which you've tested a theory.
2. Now for each subject you have predicted purchase probability, and predicted purchase probability if the program never existed ($E=E_0$ or $A=A_0$).
3. The difference is predicted incremental purchase probability from market transformation.
4. Period *n*'s contribution to market transformation load impacts is the weighted sum of (predicted incremental purchase probability) times (predicted purchase-caused savings). The latter term is estimated by applying the nonparticipant spillover device savings coefficients from the original instrumented decomposition regression. Thus:

$$\textit{market transformation load impact increment} = \sum_i w_i (1-\hat{b}_i) d_i (\hat{\alpha}_c + \hat{\beta}_n{}' X_{ni}) \qquad (8)$$

Total market transformation annual load impact in period *n* is the sum of annual spillover impacts in the first period and all annual market transformation impacts in following years, minus any adjustments for non-persistence of the evaporative coolers, or for efficiency improvements in competing technologies.

Theory 2: program incidentally spreads the word about EC. Here, Exposure is "seeing literature or ads for the EC program" and the theory is that this caused increased Awareness of EC, which causes increased purchases. The no-program value for *E* is zero. The procedure is the same as in theory 1.

Theory 3: stores stock more EC, or make them more prominent. One common theory is that in response to a rebate program and its anticipated boosting of demand, appliance stores stock more of the targeted item, or make them more accessible. Figure 4 and its associated instrumented decomposition procedure, applies, with "exposure" of an individual defined as a measure of the stocking practices of the store she shopped in for a space cooling appliance. For example, E might be a set of two variables – the percent of cooling display space allocated to EC, and the percent of people reporting their floor salesman spoke of EC. These need to be measured during-program and pre-program (preferably), or inside and outside program areas, and must be studied on people who bought EC and people who didn't.

This requires cooperation by a sample of stores, for example paying salesmen to request names and addresses of people who bought EC and people who chose another cooling method, both groups willing to be surveyed and have their billing data examined, perhaps for a fee.

Note that if we compared aggregate stocking practices to aggregate sales, we would have to consider stocking practices and sales simultaneously, as each affects the other. On individual data, however, each appliance purchaser faces a stocking practice she cannot individually influence. Unless she chooses her store based on her purchase intentions (something worth checking), causality runs from stocking practice to sales.

Example 3: Publicity Program—No Participants and Nonparticipants

Energy conservation publicity programs try to either increase demand for efficient widgets, or decrease demand for energy. They do not have participants and nonparticipants, which makes their estimation simpler.

"Flex Your Power" Campaign

Consider California's 2001 "flex your power" advertising campaign. "Exposure" might be measured as familiarity with campaign advertising, or with watching TV and not channel surfing when ads were on.

The program may cause energy savings, but other things may cause energy savings too, such as new energy awareness. Some new energy awareness will be statewide, because of the crisis. If the people surveyed have a variety of amounts of exposure to the campaign, then a simple regression of energy savings on exposure can give the savings effects of increments of exposure. (It will be the coefficient on exposure, while the intercept will capture statewide energy awareness). Net savings is the weighted sum of each sample member's exposure times the regression coefficient of exposure.

That simple regression works unless there is a situation like that in Figure 6, where people more likely to be exposed are more or less likely to have new energy awareness. In such a case you need to estimate exposure and energy savings simultaneously

First, regress Exposure on independent variables Z to get a formula for predicted exposure, $\hat{E}$, or predicted probability of exposure if E is binary. Second, regress Savings (the change in electricity bills) on independent variables X and the instrumental variable $\hat{E}$. The estimated program effect is the coefficient of $\hat{E}$.

Figure 6. "Flex Your Power" Campaign with Simultaneity

.

Widget Promotion

In the case of programs promoting a energy-saving widget, the program theory diagram is as in Figure 1, with "Exposure" replacing "Participate." That's the "Theorize" step. Next comes the Discrete choice joint estimation of Exposure and Purchase.

There are several ways of estimating jointly two simultaneous discrete choice variables. Methods that involve developing an instrumental variable $\hat{E}$ (regression-predicted exposure as a function of variables not including purchase) and then using it to estimate purchase are Amemiya's "nonlinear two-stage least squares" and the "substitution method" (both explained in Kandel and Parikh, 1996). Alternatively, you can treat the four options (exposed buyer, unexposed buyer, exposed nonbuyer, unexposed nonbuyer) as 4 choices in a nested logit model. Your method of estimating natural propensity to buy, b, will depend on the estimation method. If nested logit, use Bayes' Law. If nonlinear 2SLS or substitution, use estimated purchases with the exposure instrument set to zero.

For the Savings regression, we'll want to distinguish between program-induced widget savings, natural widget savings, and unrelated savings. The equation of estimation has a savings expression for each savings category.

$$\underbrace{s_i}_{\text{total savings}} = \underbrace{\beta_u' X_{ui}}_{\text{unrelated savings}} + \underbrace{\hat{b}_i d_i (\beta_n' X_{ni})}_{\text{natural buyer device savings}} + \underbrace{(1-\hat{b}_i) d_i (\beta_s' X_{si})}_{\text{net savings}} + \varepsilon_i \tag{8}$$

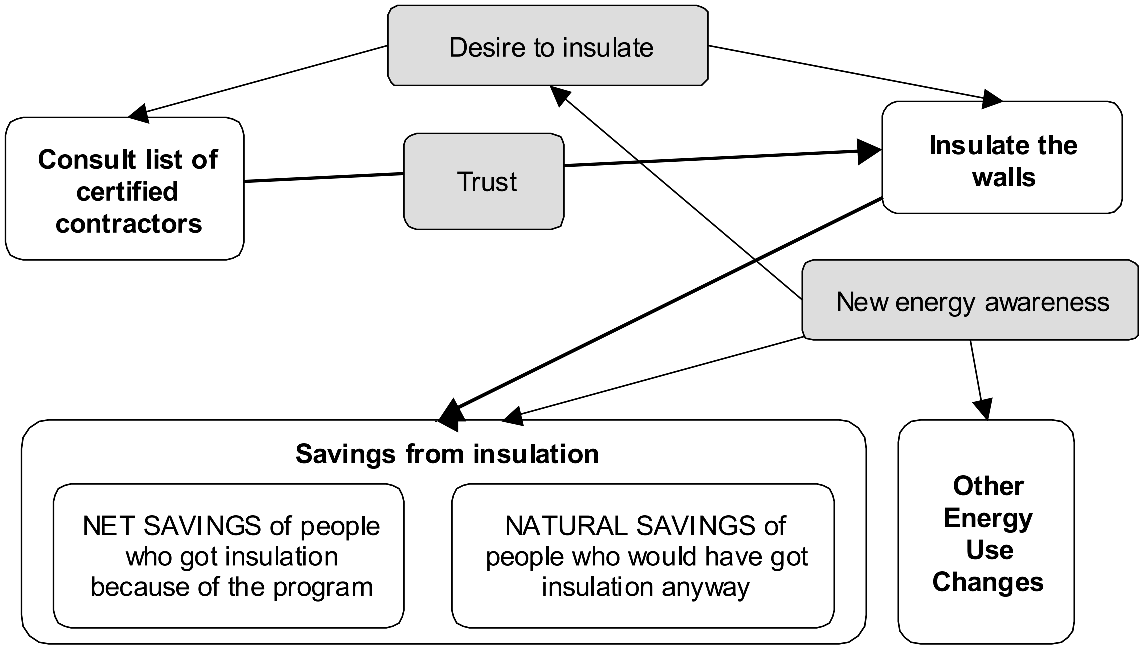
Example 4: Contractor Certification Program

Suppose a new technology for insulating walls is developed, and is not widely used because people aren't sure contractors can install the insulation correctly. In response, you set up a contractor certification program. The program theory and savings decomposition is shown in Figure 7. Here are the steps to estimating impacts.

I. Theorize

The theory is that people wishing to insulate can find a contractor in the yellow pages. Consulting the list of certified contractors, however, removes a "barrier" to insulation – mistrust of a stranger drilling holes in your wall. (Note this is not necessarily an "asymmetric information" barrier – the stranger could be incompetent but as clueless that he's incompetent as you are). Meanwhile, if you observe people consulting the list and then hiring a consultant from it and insulating, you don't know if they insulated because the list caused them to trust a contractor, or because they were already planning to insulate and just wanted to improve their contractor selection.

Figure 7. Theory of Contractor Certification List



II. Discrete Choice

Simultaneously estimate the decision to consult and the decision to insulate. There are four possibilities: consult + insulate, consult + don't insulate, don't consult + don't insulate, and insulate + don't consult. Therefore you have to use one of the estimation methods described under Example 3, for widget promotion. You then derive an estimate of *b*, the natural propensity to insulate.

III. Savings Regression

Estimate the savings from the program using the decomposition in Figure 7. You want to distinguish between the insulation-based savings of people who insulated naturally, the insulation savings of those consulted the list, and unrelated changes in energy use.

$$\underbrace{s_i}_{\substack{\text{total}\\\text{savings}}} = \underbrace{\beta_u' X_{ui}}_{\substack{\text{unrelated}\\\text{savings}}} + \underbrace{\hat{b}_i d_i (\beta_n' X_{ni})}_{\text{natural buyer insulation savings}} + \underbrace{(1-\hat{b}_i) d_i (\beta_s' X_{si})}_{\text{net savings}} + \varepsilon_i$$

Conclusion

If you have a theory of spillover or market transformation, you can design a survey to test it, collect matching billing data, and run a 2-stage instrumented decomposition regression to estimate load impacts. Your regression will correct for self-selection and free ridership, consistently. To estimate variance for this and other 2-stage regressions, see Newey (1984), explained and applied in Kandel (1999a), or contact akandel@energy.state.ca.us.

References

Imbens, G. W. 1992. "An Efficient Method of Moments Estimator for Discrete Choice Models with Choice-Based Sampling, *Econometrica*, 60(5), 1187-1214

Kandel, Adrienne Vayssières. 1999a. *Instrumented Decomposition: A New Method to Estimate the Net Energy Savings Caused by Efficient Appliance Rebate Programs.* Dissertation, U.C. Davis agricultural and resource economics department

______. 1999b. "Evaporative Cooler Rebate Program Cuts Load Significantly, and May Overcome Class Barrier*"* In *Proceedings of the 1999 International Energy Program Evaluation Conference.* Denver, 801-809

______.1999c. "Instrumented Decomposition: A Two-Stage Method for Estimating Net Savings*."* In *Proceedings of the 1999 International Energy Program Evaluation Conference.* Denver, 789-800

Kandel, Adrienne Vayssières and Kirtida Parikh. 1996. "Estimating the Effect of Exposure to Market Transformation Programs on Demand or Supply of Conservation Technology," *Residential Buildings: Program Evaluation*, volume 3 of *Proceedings: 1996 ACEEE Summer Study on Energy Efficiency in Buildings.* Asilomar. 3.51-3.58

Manski, Charles F. and Daniel McFadden. 1981. "Alternative Estimators and Sample Designs for Discrete Choice Analysis." In *Structural Analysis of Discrete Data with Econometric Applications,* Cambridge, MA: MIT Press.

Newey, W.K. 1984. "A Method of Moments Interpretation of Sequential Estimators," *Economics Letter* 14, 201-206

Parikh, K., A.V. Kandel and M. Brown. 1995. "Estimation of Spillover Effects from Energy Conservation Programs," *Energy Program Evaluation: Uses, Methods, and Results.* CONF-950817. Chicago: National Energy Program Evaluation Conference. 467-472

Seiden, Ken and Helen Platis. 1999. "Freerider and Freedriver Effects from a High-Efficiency Gas Furnace Program*."* In *Proceedings of the 1999 International Energy Program Evaluation Conference.* Denver. 227-237

Train, K., S. Buller, B. Mast, K. Parikh, and E. Paquette. 1994. "Estimation of Net Savings for Rebate Programs: A Three-Option Nested Logit Approach," *Proceedings of the ACEEE 1994 Summer Study on Energy Efficiency in Buildings*, Asilomar. 7.239-7.249

* Opinions, conclusions, and findings expressed in this report are solely those of the author. This report does not represent the views or the official position of the California Energy Commission. Any citation of the report should reference the author individually.