Instrumented Decomposition: A Two-Stage Method for Estimating Net Savings

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ABSTRACT

This paper introduces "instrumented decomposition" (ID), a two-stage method developed to analyze efficient appliance rebate programs, and to distinguish program-induced energy savings from other components of gross participant savings. The method addresses three types of self-selection effects – in appliance purchase decisions, in appliance savings given purchase, and in savings unrelated to the appliance. Based on instrumental variables rather than selection terms, ID need not assume any particular error distribution. ID does not address spillover.

Introduction

There has been much debate about the proper statistical method for measuring the "net" or program-induced energy savings caused by rebate-style programs promoting energy conservation "appliances" such as efficient appliances. This paper presents a decomposition of energy savings that clarifies the debate, and shows the biases and limitations of the methods currently in use. The decomposition allows net savings to be identified and estimated consistently in the presence of self-selection, using instrumental variables. I call the estimation procedure "instrumented decomposition," or "ID."

Instrumented decomposition is not necessary for evaluating energy conservation incentive programs that are available over a long time period, with recorded dates of program participation well dispersed over time, and with monthly billing data available for late and early participants. In such cases, a simpler panel regression of participants with time-determined participation dummy variables can estimate gross participant savings, and time dummies can control for historical trends. A separate free ridership adjustment can then yield a consistent estimate of net savings. ID addresses the case where participation dates are more clustered, so that a nonparticipant comparison group is necessary.

This paper begins by deriving ID's *Decomposition of Energy Savings*, in its most general form and in restricted forms appropriate to various data availability situations. Next it explains that *Instrumenting the Decomposition* prevents certain biases, and shows how to create "fully" and "singly" instrumented models. The paper then reviews *The Complete Instrumented Decomposition Procedure*, statistical *Treatment of the Sampling Plan*, and *Empirical Tests of ID Accuracy.* Finally, it uses ID algebra to derive the *Biases and Limitations of Other Methods of Estimating Net Savings*.

The Decomposition of Energy Savings

Vocabulary and Notation

Energy savings are defined as pre-program energy use minus post-program energy use. As shown in Figure 1, savings can be decomposed into **appliance savings** caused by use of the program-targeted appliance, and naturally occurring **trend savings** due to anything else. Appliance savings have a naturally occurring component, due to **natural buyers** who would have bought the appliance without incentive, and a program-induced component, **net savings**.

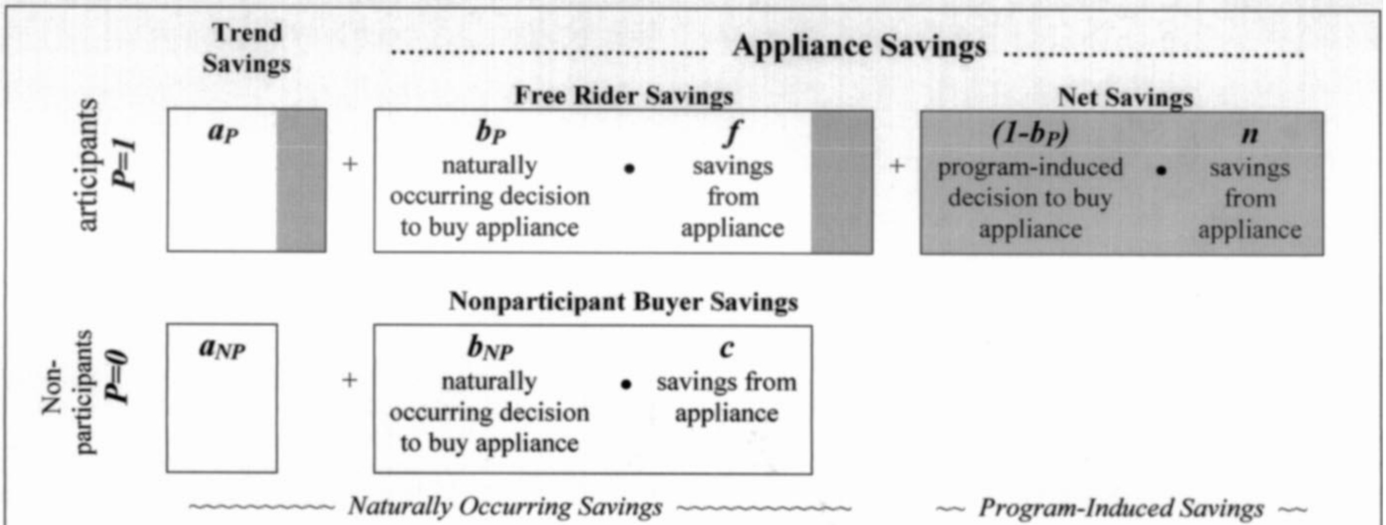

Figure 1. Participants and nonparticipants have average trend savings a_P and a_{NP}, respectively. All participants also have appliance savings, which average f for free riders (participants with natural buyership b_P=1) and n for net savers (program-induced buyers, b_P=0). Among nonparticipants, only natural buyers (b_{NP}=1) have appliance savings, which average c.

In this example, trend savings are positive and participants have higher trend and appliance savings than nonparticipants. A difference in differences procedure subtracts nonparticipant savings from participant savings, over-estimating net savings as the sum of shaded areas. ID separately identifies each savings component, so that net savings can be correctly estimated as $P(1-b_P)n$.

Variables identifying the varying types of savings are:

a_i = trend savings for household i, and may be due to socioeconomic or weather trends, or changes in the participant's household or behavior.

b_i = natural buyership, a binary variable that is one if household i would buy the appliance without program incentive. b_i=1 for participant free riders and for all nonparticipant appliance buyers.

f_i = appliance savings for free rider i, so that $b_i f_i$ represents naturally occurring appliance savings among participants.

n_i = appliance savings for program-induced appliance buyer i, so that $(1-b_i)n_i$ represents net (program-induced) savings.

c_i = appliance savings for nonparticipant i who buys the appliance.

P_i = participation, a binary variable that is one for participant households, zero for nonparticipants.

An Expression for Savings

Based on these definitions, and assuming all nonparticipant purchases would occur in the absence of the program,

$$Participant\ Savings_i = a_i + b_i f_i + (1-b_i)n_i \tag{1}$$

$$Nonparticipant\ Savings_i = a_i + b_i c_i \tag{2}$$

Using the participation indicator variable P to combine equations (1) and (2),

$$Savings_i = s_i = \underbrace{a_i}_{\substack{trend\\savings}} + \underbrace{(1-P_i)b_i c_i}_{\substack{nonparticipant\ buyers'\\appliance\ savings}} + \underbrace{P_i b_i f_i}_{\substack{free\ riders'\\appliance\ savings}} + \underbrace{P_i(1-b_i)n_i}_{net\ savings} \qquad (3)$$

Expressions for Savings Components

Each savings component can be expressed as a function of relevant independent variables X plus an error term:

$$a_i = \gamma'_a X_{ai} + \varepsilon_{ai} \qquad c_i = \gamma'_c X_{ci} + \varepsilon_{ci} \qquad f_i = \gamma'_f X_{fi} + \varepsilon_{fi} \qquad n_i = \gamma'_n X_{ni} + \varepsilon_{ni}$$

Trend savings variables X_{ai} may reflect weather, social, and economic trends, household i's socioeconomic characteristics, and changes in i's stock of energy-using equipment. Appliance savings variables X_c, X_f and X_n may include factors relating to usage of the appliance (such as family size for washing machines), and characteristics of the appliance it may be replacing (such as age), as well as building envelope characteristics for heating and cooling appliances.

The General Decomposed Expression for Energy Savings

Substituting the definitions of a, c, f, and n into equation (3),

$$s_i = \underbrace{(\gamma'_a X_{ai} + \varepsilon_a)}_{trend\ savings} + \underbrace{(1-P_i)b_i(\gamma'_c X_{ci} + \varepsilon_{ci})}_{\substack{nonparticipant\ buyer\\appliance\ savings}} + \underbrace{P_i b_i(\gamma'_f X_{fi} + \varepsilon_{fi})}_{\substack{free\ rider\\appliance\ savings}} + \underbrace{P_i(1-b_i)(\gamma'_n X_{ni} + \varepsilon_{ni})}_{\substack{net\ saver\ appliance\ savings\\= net\ savings}}$$

or:

$$s_i = \gamma'_a X_{ai} + (1-P_i)b_i\gamma'_c X_{ci} + P_i b_i \gamma'_f X_{fi} + P_i(1-b_i)\gamma'_n X_{ni} + \varepsilon_i^*, \qquad (4)$$

where $\varepsilon_i^* = \varepsilon_{ai} + (1-P_i)b_i\varepsilon_{ci} + P_i b_i \varepsilon_{fi} + P_i(1-b_i)\varepsilon_{ni}$.

This is a regression equation, describing the effect of independent factors on total savings. To estimate it, one would need observations in each appliance buyer category (nonparticipant buyer, free rider and net saver), as well as observations of nonparticipants who do not buy the appliance. The nonparticipant nonbuyers—who have no appliance savings—are necessary to distinguish trend from appliance savings and identify $\gamma_a X_a$. That way, each buyer group's appliance savings can be identified as the difference between its total savings and its trend savings.

Restricted Decompositions

Equation (4) involves a large number of correlated regressors, and probably should be condensed using restrictions. This section presents some useful restricted models.

When Nonparticipant Program-Year Buyers are Observed. For discrete choice estimation of free ridership, it has been common to seek out and find program-year nonparticipant buyers of the program-targeted appliance. Such nonparticipant buyers may have been unaware of the rebate program, unwilling to handle program paperwork, or ineligible. A data set that includes such nonparticipant buyers may be used to condense the general decomposition if participant and nonparticipant natural buyers have the same expected savings from the appliance, after correcting for observed differences in their independent variable values. The two natural buyer groups will be able to share one appliance savings expression: $X_c=X_f$ and $\gamma_c=\gamma_f$ so that equation (4) reduces to

$$s_i = \underbrace{\gamma'_a X_{ai}}_{\substack{trend\\ savings}} + \underbrace{b_i \gamma'_c X_{ci}}_{\substack{natural\ buyer\\ appliance\ savings}} + \underbrace{P_i(1-b_i)\gamma'_n X_{ni}}_{net\ savings} + \underbrace{\left(\varepsilon_a + b_i\varepsilon_c + P_i(1-b_i)\varepsilon_n\right)}_{\varepsilon_i{}^*} \quad (5)$$

When Nonparticipant Appliance Owners are Observed, Date of Purchase Unknown. It may be hard to identify many nonparticipants who bought the appliance during the program-year, but it may be easy to find nonparticipants who have the appliance. An unknown proportion of them will have bought the appliance during the program year, and only that proportion will show appliance savings on their energy bills that year. Therefore nonparticipants will register less appliance savings on average than participant natural buyers, and cannot share one natural buyer savings expression. This is the case for the evaporative cooling rebate program described in Kandel (1999a and 1999b, Chapter 6).

In this case, a different restriction is needed to limit multicollinearity: have all participants share a set of appliance savings variables X_P with shared coefficients γ_P. The average difference in appliance savings between the two types of participants is then captured in separate free rider and net saver intercepts, γ_f and γ_n. The savings expressions are:

nonpart. appliance savings	*free rider appliance savings*	*net savings*
$c_i = \gamma'_c X_{ci} + \varepsilon_{ci}$,	$f_i = \gamma_f + \gamma'_p X_{pi} + \varepsilon_{fi}$,	$n_i = \gamma_n + \gamma'_p X_{pi} + \varepsilon_{ni}$

Meanwhile, b takes on a new definition: naturally occurring *ownership* rather than naturally occurring program-year purchase of the appliance. Free riders become participants who without program incentive would have owned the appliance by the time the program was over. They remain a group of participants who do not contribute to net savings. The new savings equation is:

$$\underbrace{s_i}_{\substack{total\\ savings}} = \underbrace{\gamma_{ai}{}' X_a}_{\substack{trend\\ savings}} + \underbrace{(1-P_i)b_i\gamma_{ci}{}' X_c}_{\substack{nonparticipant\ owner\\ appliance\ savings}} + \underbrace{P_i b_i \gamma_f + P_i(1-b_i)\gamma_n + P_i\gamma_{pi}{}' X_p}_{participant\ appliance\ savings} + \varepsilon_i{}^* \quad (6)$$

where $\varepsilon_i{}^* = \varepsilon_a + (1-P_i)b_i\varepsilon_{ci} + P_i b_i \varepsilon_{fi} + P_i(1-b_i)\varepsilon_{ni}$ as in equation (4).

This ID variation is also useful if there are too few program-year nonparticipant buyers to make statistical inference, but there are plenty of pre-program buyers. In that case, any available information about which nonparticipants bought their appliance during the program year and which ones bought beforehand can be used as a binary nonparticipant appliance savings variable, part of X_c.

When Nonparticipant Appliance Owners are Observed, Purchases All Before Program. A special case arises when all nonparticipant owners of the program-targeted appliance bought it before the program year. Their appliance savings — the pre- to post-program energy use change due to the appliance — are zero, so that the middle term drops out of the right hand side of equation (6):

$$\underbrace{s_i}_{\substack{total\\ savings}} = \underbrace{\gamma_{ai}{}' X_a}_{\substack{trend\\ savings}} + \underbrace{P_i b_i \gamma_f + P_i(1-b_i)\gamma_n + P_i\gamma_{pi}{}' X_p}_{participant\ appliance\ savings} + \underbrace{\varepsilon_a + P_i b_i \varepsilon_{fi} + P_i(1-b_i)\varepsilon_{ni}}_{\varepsilon_i{}^*} \quad (7)$$

If the researcher does not know whether all nonparticipant owners bought their appliance before the program began, he or she can test whether the nonparticipant appliance savings terms go to zero in the final regression.

Instrumenting the Decomposition

The Need for Instruments

Equations (4) through (7) generally cannot be estimated using an ordinary least squares regression for two reasons:

1. Natural buyership-or-ownership b is either unobservable for participants or measured with considerable error via (hypothetical) self-report. Measurement error in a regressor component causes bias and inconsistency.
2. Error component ε_a will be correlated with regressors if unexplained factors ε_a in trend savings affect either the participation or the natural buyership decisions. That is, the equation is vulnerable to self-selection bias in trend savings, since all participants and nonparticipants are constrained to the same trend savings expression $\gamma_a X_a + \varepsilon_a$. (The equation is *not* vulnerable to self-selection bias in appliance savings, since each buyer type is given its own appliance savings expression.)

The Fully Instrumented Regression

The "fully instrumented regression" I propose will solve both problems by using instrumental variables. In a first stage, purchase decisions are regressed on independent variables to create equations defining $\hat{P}$ and $\hat{b}$, the predicted probabilities of P and b. In a second stage those predicted probabilities become "instruments", replacing P and b. For example equation (6), is replaced by:

$$s_i = \gamma_{ai}{}' X_a + (1-\hat{P}_i)\hat{b}_i\gamma_{ci}{}' X_c + \hat{P}_i\hat{b}_i\gamma_f + \hat{P}_i(1-\hat{b}_i)\gamma_n + \hat{P}_i\gamma_{pi}{}' X_p + \varepsilon_i{}^* \tag{8}$$

No particular assumptions about the distribution of the error term are required (Heckman and Robb, 1985, p. 185), but the instruments must be correlated with the true P and b they represent and uncorrelated with the error term. Since regression-predicted probabilities are necessarily correlated with P and b, the crucial consistency requirement is that instruments be independent of ε^*, which captures the factors that influence savings, s, but are omitted from the independent X variables. Therefore, if any independent variable predicting P or b in the first-stage regression also influences savings, s, it must not be omitted from second-stage X variables. Since the instruments are pure functions of first-stage regressors, that condition is sufficient to ensure independence between the instruments and ε^*.

A review of conditions under which the full set of regressors is orthogonal to the composite error term (Kandel 1999b, chapter 3) will also show that any variable which influences both trend and appliance savings cannot be included as a regressor for only one of those types (if it is in X_c or X_p it must be in X_a, and vice-versa). Otherwise, the model will not correctly distinguish between trend and appliance savings.

Finding the Instruments: Joint Estimation of $\hat{P}$ and $\hat{b}$ in the First-Stage Regression

To estimate $\hat{P}$ and $\hat{b}$, one can use the nested logit method proposed by Train et al. (1994) to estimate free ridership, which is the unobserved natural buyership b among participants. The method uses an observed appliance purchase (or ownership) indicator variable, d. A household has three choices (numbered from zero):

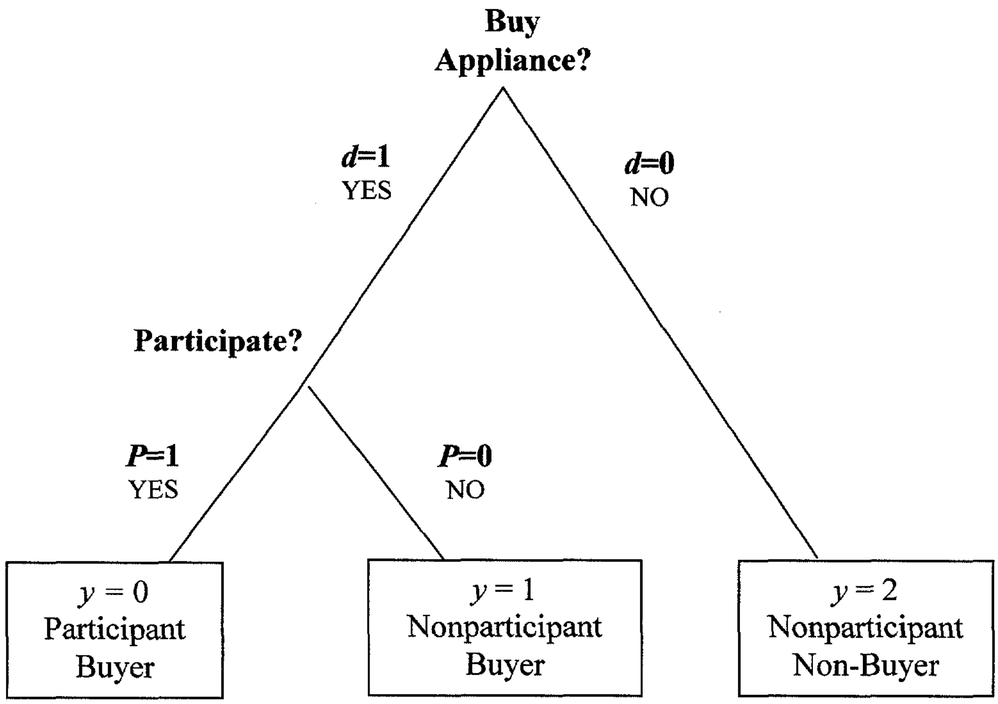

Figure 2. The basic nested logit model. y is the choice and the branch number.

(0) To be a participant who purchases an appliance *(d=P=1)*.
(1) To be a nonparticipant who purchases an appliance *(d=1,P=0)*, or
(2) To be a nonparticipant with no appliance *(d=P=0)*.

The data set must contain observations in all three categories. When the nonparticipant data set cannot identify program-year nonparticipant buyers, d will represent ownership by the time the program is over, rather than program-year purchase.

The nested logit decision tree is shown in Figure 2, and does not imply sequential decision-making. Rather, it depicts error correlation between choices (0) and (1). It allows for the possibility that if choice (1) were removed, for example, households now making that choice would be more likely to make choice (0) than choice (2).

After the regression is run, b is estimated by noting that b is the probability that a household would buy the appliance without incentive, or

$$\Pr(b_i = 1) = \Pr(d_i = 1 | P_i = 0) = \frac{\Pr(d_i = 1 \; and \; P_i = 0)}{\Pr(P_i = 0)}$$

Thus $\hat{b}$ is the regression-predicted probability of branch (1), divided by the sum of the predicted probabilities of branches (1) and (2). $\hat{P}$ is the predicted probability that branch (0) is chosen.

The Singly Instrumented Model

Empirical tests and simulations suggest that when participants constitute much less than 10% of the population, $\hat{P}$ will be near zero for all households, and will vary too little to be a good instrument. In that case, net savings will be estimated with prohibitively large variance (Kandel, 1999b chapter 6).

It becomes necessary to use the true variable P rather than the instrument $\hat{P}$, making the model "singly instrumented."

$\hat{b}$ and $\hat{P}$ remain jointly estimated, along with $\hat{d}$, but only $\hat{b}$ is used in the second-stage regression. (This does *not* mean that in the first stage, one random process is assumed in deriving the instrument $\hat{b}$ and another is assumed to derive the variable P. Rather, it means that in the second stage, trend savings is assumed to be independent of the participation decision outcome. As in the fully instrumented model, trend savings need not be independent of the naturally occurring purchase decision, b, and appliance savings need not be independent of either P or b.)

In other words, the singly instrumented model is consistent only if there is no participant self-selection effect in trend savings, after controlling for observed X_a variables. Model estimates will be biased if unobserved factors that affect trend savings also affect the participation decision. An example of such an unobserved factor would be a remodeling decision unrecorded in the data, and therefore unavailable as an independent variable.

While one can never be sure that all factors influencing both trend savings and the participation decision are observed, there are many cases where it is reasonable to assume unobserved factors play only a minor role. In such cases, if population participation rates are low, the small bias of the singly instrumented model will be preferable to the large variance of the fully instrumented model.

The singly instrumented regression based on equation (6) and applied in Kandel (1999a) is

$$s_i = \gamma_{ai}{}' X_a + (1-\hat{P}_i)\hat{b}_i \gamma_{ci}{}' X_c + P_i \hat{b}_i \gamma_f + P_i(1-\hat{b}_i)\gamma_n + P_i \gamma_{pi}{}' X_p + \varepsilon_i{}^* \tag{9}$$

The Complete Instrumented Decomposition Procedure

The complete instrumented decomposition procedure, then, is:

I. Jointly estimate $\hat{P}$ and $\hat{b}$ using a nested logit regression.

II. Use $\hat{b}$ and possibly $\hat{P}$ as interaction terms in a linear savings regression.

III. Use regression results to estimate net savings and other quantities of interest.

Net Savings

Once the regressions are performed, net savings can be estimated for each household i and then summed over all households. If the sample is stratified, a weighted average is used; the weight attached to household i is [fraction of population in i's stratum]/[fraction of sample in i's stratum].

If equation (4) or (5) is used, household i's net savings are

$$\textit{Net Savings}_i = P_i\left(1-\hat{b}_i\right)\left(\tilde{\gamma}'_n X_{ni}\right)$$

where $\tilde{\gamma}_n$ is the 2nd stage regression estimate of γ_n. If equation (6) or (7) is used, net savings are

$$\textit{Net Savings}_i = P_i\left(\tilde{\gamma}_n + (1-\hat{b}_i)\tilde{\gamma}'_p X_{pi}\right)$$

Variance

Asymptotic variance formulas for net savings as well as parameter estimates can be found in Kandel (1999b), Appendices A through C, or obtained from this author at akandel@energy.state.ca.us. They use Newey's (1994) method of moments variance estimator for two-stage procedures. I can also provide Gauss programs implementing the fully and singly instrumented versions of equation (6). Alternatively, one could use the bootstrap method, but repeated nonlinear optimizations will take time.

Treatment of the Sampling Plan

Most evaluations of energy efficiency programs will involve choice-based samples, with participants over-sampled so that they can be studied. Nested logit and other discrete-choice regressions must compensate for this over-sampling of participants, or they will over-predict participation. In linear regressions also, stratification schemes correlated with the dependent variable will cause bias and inconsistency.

One method of ensuring consistency is to weight each observation *i* by [population fraction in *i*'s stratum]/[sample fraction in *i*'s stratum]. Unfortunately, this procedure defeats the purpose of intentional over-sampling. In my evaporative cooling empirical work (Kandel 1999a), for example, it would bring the effective participant sample down from 476 to 9, a number too small for effective inference.

A preferable alternative is to purge the regression noise of correlation with the independent variable by including as regressors variables that drive the sampling plan, for example stratum-specific dummy variables. This method will work for ID's second-stage linear regressions, and for most of the stratification variables in the first stage nested logit regression. The method will not handle choice-based stratification in the nested logit stage, however, because one cannot include a dependent variable – participation – as a regressor.

For the nested logit regression, one needs to apply a maximum likelihood function that incorporates the sampling probabilities. The exact likelihood function is computationally difficult, so I applied Manski and McFadden's consistent but not efficient conditional maximum likelihood estimator ("MM"). MM would be maximum likelihood under the false condition that the independent variables were fixed, rather than randomly drawn along with dependent variable values in a survey.

MM does not weight each observation's contribution to the log likelihood sum; hence, it does not lower the effective participant sample size. Instead, it <u>adds</u> a sampling distortion correction to the log likelihood function, so the relative importance of differing sample members is not changed. In my empirical tests, the MM method yielded standard errors about 100 times smaller than weighting.

Algebraic formulas can be found in Manski and McFadden (1981) or in Kandel (1999b), chapter 5; some Gauss programs are available from this author.

It turns out that to calculate the MM estimator, one needs to know the population size for each stratum, but not necessarily for each choice that does not constitute a full stratum. For example, I applied MM on a data set with a stratified sample of the general population combined with a simple random sample of participants. Therefore I did not know the population size of nonparticipant buyers.

Empirical Tests of ID Accuracy

I applied the singly instrumented method to two residential rebate programs – evaporative cooling and central air conditioning – and results were encouraging. Standard errors were only 12 to 24% of the net savings estimate. Sensitivity to variable choice was low, with results changing 15 to 35% when different sets of independent variables are used. Gross appliance savings estimates fell in the range predicted by engineering estimates, and free ridership rates were believable. Both of these applications are detailed in Kandel (1999b, chapters 6 and 7), with the evaporative cooling program evaluations also summarized in Kandel (1999a), in these proceedings.

Biases and Limitations of Other Methods of Estimating Net Savings

The first section of this paper used the decomposition of savings to derive a method of estimating net savings with little or no bias. The following section will use the decomposition algebra to clarify the implicit assumptions of some net savings estimation methods currently in use, also based on the differences between participant and nonparticipant savings.

Simple Difference in Differences

In Figure 1 above, the shaded area shows the net savings predicted using the simple difference in differences method:

(Average savings per participant) - (Average savings per nonparticipant) =

$$\underbrace{\left(\overline{a}_P + \overline{\left(b_P f\right)} + \overline{\left(1-b_P\right)n}\right)}_{\substack{\textit{participant} \\ \textit{average savings}}} - \underbrace{\left(\overline{a}_{NP} + \overline{\left(b_{NP}c\right)}\right)}_{\substack{\textit{nonparticipant} \\ \textit{average savings}}} = \underbrace{\left(\overline{a}_P - \overline{a}_{NP}\right)}_{\substack{\textit{difference in} \\ \textit{trend savings}}} + \underbrace{\left[\overline{\left(b_P f\right)} - \overline{\left(b_{NP}c\right)}\right]}_{\substack{\textit{difference in naturally} \\ \textit{occurring appliance savings}}} + \underbrace{\overline{\left(1-b_P\right)n}}_{\textit{net savings}}$$

This reduces to the correct value of $\overline{\left(1-b_P\right)n_P}$ under the following assumptions:

(A1) Participants have the same average trend savings as nonparticipants: $\overline{a}_P = \overline{a}_{NP}$.

If this condition is not met, the difference in trend savings between the two groups will be incorrectly attributed to program-induced appliance savings.

(A2) Participants have the same average naturally occurring appliance savings as nonparticipants:

$\overline{b_P f} = \overline{b_{NP} c}$

This condition generally requires that:

(a) Participants and nonparticipants have the same natural buyership process, b, and

(b) Participants and nonparticipants have the same appliance savings process for natural buyers (f and c are equivalent).

Note that free riders must have the same average appliance savings as nonparticipant buyers, but program-induced buyers can have different expected savings without causing bias.

Regression Difference in Differences

The regression difference in differences is a linear regression of the form: $savings = X\gamma + \alpha P + \varepsilon$, where P is a participation indicator variable, and is like taking a simple difference of differences after controlling for the effects of independent variables X. It can be shown (Kandel 1999b, chapter 4) that the conditions for consistency are:

(A1′) Participants have the same expected trend savings noise as nonparticipants.

(A2′a) Participants and nonparticipants have the same natural buyership process, b.

(A2′b) Like participants and nonparticipants have the same expected appliance savings ($\gamma_c = \gamma_f$).

The consistency conditions for difference in differences methods can be viewed as ruling out various types of self-selection bias. (A1) and (A1′) rule out self-selection bias in trend savings. (A2) and (A2′) rule out self-selection bias in appliance savings, via (a) differing natural purchase behaviors between participants and nonparticipants, and (b) differing savings given appliance purchases.

With one self selection correction term

Researchers generally understand that there may be self-selection bias in comparing participants and nonparticipants, and many have applied a Heckman-style self-selection correction term. Unfortunately, this remedy is based on an imperfect analogy. Heckman (1979) devised his self-selection correction term to measure the effect of labor training programs on trainees' incomes. In these programs, it is impossible to get the training without being a participant; thus free ridership cannot exist.

In terms of this paper's savings decomposition, Heckman's algebra assumes $b = 0$, always. Consequently, Heckman's method cannot address correlation between P and b, the case of self-selection in natural appliance savings via differing natural buyership tendencies. Goldberg and Train (1995) note this failure is critical, because participation probably is correlated with the natural tendency to buy the appliance and with appliance savings.

With random participation coefficient

Goldberg and Train suggested that the true savings process involves a random parameter for net savings, because different households have different natural tendencies to buy. The savings process could be described by having b as an element of the net savings term, as in the decomposition of equations (4) through (7). Goldberg and Train show that adding a second selection term, interacted with the participation variable, handles the simultaneity between random participation effects and their regressor P.

The limiting assumption is the distribution assumed for the selection term; so far selection terms have been derived only for unimodal net savings distributions. Thus the Goldberg-Train method cannot be applied to single-appliance rebate programs, where the net savings distribution is bimodal—with one spike near zero for free riders and another hump for program-induced buyers around average appliance savings.

Difference in differences, times free ridership correction

Another method used to estimate net savings is multiplying the difference in differences estimator by a net-to-gross ratio (one minus the proportion of free ridership). First, the difference in differences estimator predicts savings for participant i of

$$\begin{aligned} D_i &= \text{participant } i\text{'s gross savings minus a similar nonparticipant's gross savings} \\ &= \left[a_{Pi} + b_{Pi} f_i + (1-b_{Pi})n_i\right] - \left[a_{NP} + b_{NP}c\right] \\ &= (a_{Pi} - a_{NP}) + (b_{Pi} f_i - b_{NP}c) + (1-b_{Pi})n_i \end{aligned}$$

Then, at best, the net-to-gross ratio is applied observation by observation, so that D_i is multiplied by one minus its predicted free ridership ratio, or $(1 - b_{Pi})$, so that (ignoring random noise):

$$\textit{estimated net savings}_i = (1-b_{Pi})\left[(a_{Pi} - a_{NP}) + (b_{Pi} f_i - b_{NP}c) + \underbrace{(1-b_{Pi})n_i}_{\textit{actual net savings}}\right] \tag{10}$$

For equation (10) to reduce to net savings $(1 - b_{Pi})n_i$ the following conditions must be true:

(B1) Similar participants and nonparticipants have same expected trend savings, so that $a_{Pi} - a_{NP} = 0$.
(B2) Nonparticipants have zero naturally occurring appliance savings b_{NPC}, so that they do not control for any free ridership before the net-to-gross ratio is applied.
(B3) Appliance savings are the same for like free riders and net savers ($f_i = n_i$).

Summary

ID is based on a decomposition of savings after a single-appliance incentive program into its trend and appliance-related components. Appliance savings are further decomposed by buyer type: nonparticipant buyers, free riders and net savers. Each savings component depends linearly on a set of independent variables, which may or may not be shared with other savings components. The ID procedure is:

I. In a nested logit regression, jointly estimate the probability of participating in a conservation program, $\hat{P}$, and the probability of buying an appliance without program incentive, $\hat{b}$.

II. Use these predicted probabilities as instruments in interaction terms to decompose savings into program-induced and naturally occurring components in a second stage energy savings regression, based on one of equations (4) through (7). If participants are not numerous in the population it may be necessary to use a true participation indicator variable P, in lieu of the instrument $\hat{P}$. In that case, a left-out factor that influences both trend savings and the participation decision can cause bias.

III. Estimate net savings for each participant surveyed, and sum them to get total net savings (use a weighted sum if the participant sample is stratified).

To ensure consistency, the researcher must see to it that:

1. Any regressor predicting participation or purchase as well as savings is included in both the first and second stage regressions, or in neither. (Both is better.)
2. Any variable that influences both trend and appliance savings is included in the expressions for both, or in neither.

The ID procedure has many advantages. Participant self-selection in the decision to buy the appliance is handled by the nested logit regression, as shown by Train et al (1994). Self-selection in trend savings is handled by the instrumentation of P, when population sample sizes permit, and/or by including variables such as remodeling which might affect both the participation decision and trend savings. Self-selection in appliance savings is handled by the separate treatment of each buyer type. Free ridership is handled by the instrumentation of b to form participants' predicted probability of being free riders, $\hat{b}$. The decomposition allows $\hat{b}$ to be correctly applied to appliance savings only, and not to appliance-unrelated trend savings. Finally, the instrumental variable procedure does not require any particular distribution for net savings or for regression errors.

In contrast the simple difference in differences estimator is vulnerable to differences between participants and nonparticipants in the decision to buy naturally, in trend savings, and in appliance savings of natural buyers. The regression difference in differences is vulnerable to what dissimilarities remain after controlling for observed X variables. The Heckman correction was developed for programs where free ridership was impossible, and does not apply to most energy conservation programs. The Goldberg-Train estimator has none of the above flaws, but so far its algebra has only been developed for programs with a unimodal net savings distribution, unlikely in single item rebate programs.

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