Evaluating Information Programs when Outcomes are Discrete:

Energy Audit Programs and Household Energy Retrofit Activity

by

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ABSTRACT

Sometimes policy makers seek to influence economic activity by providing information, rather than by manipulating relative prices. We formulate a utility-theoretic model for households' decisions to install attic insulation with and without participation in an energy audit program. A *joint* discrete dependent variable model (with FIML estimation) is employed to correct for selectivity bias in assessing program effects. We find that (i.) self-selection bias gives the audit program roughly twice the credit it deserves, and (ii.) policy measures designed to influence retrofit costs or energy prices appear to have more-discernible *direct* effects on retrofit activity than do audit programs.

1. Introduction

Not all programs designed to influence the behavior of economic agents manipulate relative prices until the optimal strategy for the household more nearly corresponds to the objectives of society as a whole. Some are intended only to reduce households' *uncertainty* about the costs and benefits of taking some action. "Energy audit" programs, which have been widely advocated, are one example. By providing reliable information, they are intended to increase energy conservation retrofit activity even though the actual costs and benefits are unchanged. How successful have energy audit programs been in stimulating retrofit activity? And how do audit programs compare with alternative market-oriented methods for encouraging greater retrofit activity?

In formulating a retrofit decision model, we can adapt the empirical strategies used by labor economists, who are very familiar with the problem of assessing the net effectiveness of manpower training programs.[1] Self-selection bias is an important consideration in these models. However, the outcome variable in labor models (earnings) is a continuous variable; in the retrofit case, it is discrete.

A general microeconometric model for explaining retrofit activity is presented in section 2, where we describe an estimation method appropriate to discrete choice models with self-selection. Section 3 outlines our available data and Section 4 specializes the theoretical model for estimation. Section 5 describes and evaluates the separate and joint models of retrofit activity and audit participation, and section 6 puts the fitted model to work in a set of simulation exercises.

2. Modeling Energy Audits and Household Conservation Retrofits

Cameron (1985) examines household retrofit decisions in a utility-theoretic choice model using a nationwide sample for 1977-78, but this study predates widespread availability of retrofit inducement programs such as tax credits, energy audits, and low-interest guaranteed loans. Hartman and Doane (1986) estimate *ad hoc* models of participation in both energy audit programs and low-interest loan programs. In their retrofit decisions, however, cross-alternative variability is provided solely by estimated *savings* under each retrofit combination (as no independent cost data are available). They attempt to accommodate program participation endogeneity in their *electricity consumption* model only.[2]

In contrast, this research emphasizes a fully utility-theoretic specification for a household's simple discrete choice regarding whether or not to install attic insulation. To maximize estimation efficiency, the potential endogeneity of the audit participation decision as a determinant of retrofit decisions will be accommodated in a one-stage full information maximum likelihood (FIML) estimation technique.

A recent labor economics example of a selectivity correction procedure (Bjorklund and Moffitt, 1987) seems well-suited for adaptation to our discrete case. In the context of energy retrofit decisions, the continuous earnings variable (Y_1) is replaced by an unobservable "propensity to retrofit" variable, which we interpret as the "utility difference due to retrofitting." Assume that each household's retrofit decision is based on the level of indirect utility it expects to enjoy with and without the retrofit. Households derive utility from "space heating," "space cooling," and a composite of "all other goods and services." We view a house as a structural shell which retains heat (during space heating) and prevents heat gain (during cooling). Fuel (or electricity) is required to operate heating or cooling equipment, but fuel inputs do not themselves confer utility. Only when they are combined with the capital services of the heat generating (or removal) equipment and the structural shell do they result in the "space comfort" outputs which do provide utility.

As in Cameron (1985), we first consider each household's expenditures on heating and cooling fuel. Demands for these inputs will be derived from their demands for space heating and space cooling:

(1) heating: $(PF_h)f_h = PF_h\ (1/E_h)\ U\ (\ HDD_i - HDD_o)$

cooling: $(PF_c)f_c = PF_c\ (1/E_c)\ U\ (\ CDD_o - CDD_i)$

where PF_h and PF_c are the per-unit prices of the household's primary heating fuel and cooling fuel, respectively; f_h and f_c are the nominal quantities of heating and cooling fuel; E_h and E_c are the approximate efficiencies of the heating and cooling equipment; U is the total "lossiness" of the structural shell (in BTU's per degree day); HDD_o and HDD_i are outside and inside heating degree days per year; CDD_o and CDD_i are outside and inside cooling degree days per year. Decisions regarding the two types of capital--heat generating (or removal) equipment and the structural shell--are considered medium-to-long-run investment decisions. The amount of temperature compensation is a short-run consumption decision (i.e. thermostat-setting behavior). Local variations in climate will be the primary determinant of the amount of heating $(HDD_i - HDD_o)$ and cooling $(CDD_o - CDD_i)$ households actually consume.[3]

Indirect utility will depend on the household's opportunity sets under each retrofit alternative, which reflect income net of retrofit costs, Y - C, and the "prices" of marginal units of space heating or space cooling: $p_h = PF_h\ (1/E_h)\ U$ and $p_c = PF_c\ (1/E_c)\ U$.

The total U factor in each marginal price will depend upon the size of the house, its configuration, and the materials from which it is constructed. But it will also depend upon the household's decision regarding whether or not to retrofit for energy conservation. By retrofitting, the household gives up some income but also decreases its prices of heating and cooling by reducing the lossiness of the structural shell. If the *ex ante* expected changes in the slopes of the opportunity set boundary are sufficient, households may perceive that the maximum level of utility they can attain *with* the retrofit exceeds that attainable under the status quo, and they would retrofit. From each household's decision, we can infer something about the configuration of households' indirect utility function, V*.

A household will retrofit if $V^*(Y - C, p_h^a, p_c^a)$ exceeds $V^*(Y, p_h^b, p_c^b)$, where, C is cost of the retrofit measure and the superscripts on the prices denote the "after-retrofit" (a) and "before-retrofit" (b) prices of space heating and space cooling (and we ignore for now the effect of the audit program). However, we cannot fully observe the determinants of V*, so we assume that utility can be decomposed into an observable component, V, and an unobservable component, ϵ. We can then write:

$$(2) \quad Pr(retrofit) = Pr [V(Y - C, p_h^a, p_c^a) + \epsilon_1 > V(Y, p_h^b, p_c^b) + \epsilon_0],$$
$$= Pr [(\epsilon_0 - \epsilon_1) < V(Y - C, p_h^a, p_c^a) - V(Y, p_h^b, p_c^b)]$$

where the error difference $(\epsilon_0 - \epsilon_1)$ is now treated as a single normally distributed random variable.

Without an audit, households face uncertain costs and savings from retrofitting. Because retrofit savings and cost information is commonly given in per-square-foot terms, total uncertainty is likely to be proportional to the square footage of the house. We assume that the expected values of retrofit costs and savings match the "certainty" values provided by the audit but that, because of uncertainty, retrofitting without an audit is a "gamble." With risk aversion, the utility from the gamble will be lower than that from the expected levels with certainty. Thus, we assume that ex ante anticipated post-retrofit indirect utility differs systematically between audited and non-audited households by an additive "uncertainty reduction" term, proportional to square feet. The coefficient on this variable should be positive.

But the decision to take an energy audit is not necessarily exogenous. Volunteering to take an audit may imply relatively stronger "energy awareness" which may also be positively correlated with retrofit activity. Self-selection into the audit program could seriously bias the audit coefficient in a simple discrete choice model for the retrofit decision.

Our submodel for audit program participation assumes that there are both benefits and costs associated with taking an audit. The increase in expected post-retrofit indirect utility due to uncertainty reduction is the primary "benefit" of an audit (α_i). The costs (ϕ_i) reflect the inconvenience of *arranging* for the retrofit--someone must be at home to admit the auditors and their equipment. Thus, the opportunity cost of time (i.e. income) will inversely affect the probability of taking an energy audit. It is also costly to *find out* about the advantages of audits. Less-educated households may be less well-informed, so the educational attainment of the household head is also included.

Our full retrofit model with its discrete outcome variable can be made explicit as follows.[4] Unobservable variable Y_i^*, equal to $V(Y-C,p_h^a,p_c^a)$ - $V(Y,p_h^b,p_c^b)$, is the amount by which the household's anticipated indirect utility *with* the retrofit exceeds that without it. The observable manifestation of Y_i^* is Y_i. If $Y_i^* > 0$, the household retrofits ($Y_i = 1$);

otherwise, the household does not retrofit ($Y_i = 0$). T_i^* is an unobservable continuous variable which we will call the household's "propensity to take an energy audit." T_i takes on a value of one if T_i^* is positive (audit) and zero if T_i^* is negative (no audit). The exogenous variables affecting the retrofit decision are X_i; the benefits of an audit are Z_i, and the costs of an audit are W_i. The structure of the model is:

(3) $Y_i = 1$ if $Y_i^* > 0$; $Y_i = 0$ otherwise

(4) $Y_i^* = x_i\beta + \alpha_i T + \epsilon_i$

(5) $T_i = 1$ if $T_i^* > 0$; $T_i = 0$ otherwise

(6) $T_i^* = \alpha_i - \phi_i$

(7) $\alpha_i = Z_i\delta + u_i$

(8) $\phi_i = W_i\eta + v_i$

$$E(\epsilon_i^2) = \sigma_e^2, \quad E(u_i^2) = \sigma_u^2, \quad E(v_i^2) = \sigma_v^2$$

$$E(\epsilon_i u_i) = \sigma_{eu}, \quad E(\epsilon_i v_i) = \sigma_{ev}, \quad E(u_i v_i) = \sigma_{uv}$$

In reduced form, the model can be written as:

(9) $Y_i = 1$ if $Y_i^* > 0$; $Y_i = 0$ otherwise

(10) $Y_i^* = X_i\beta + Z_i\delta + (\epsilon_i + u_i) = X_i\beta + Z_i\delta + e_i$ if $T_i = 1$

(11) $Y_i^* = X_i\beta + \epsilon_i$ if $T_i = 0$

(12) $T_i = 1$ if $T_i^* > 0$; $T_i = 0$ otherwise

(13) $T_i^* = Z_i\delta - W_i\eta + (u_i - v_i) = Z_i\delta - W_i\eta + f_i$

Akin to Maddala (1983, p. 223-224), we assume that ϵ_i, e_i ($= \epsilon_i + u_i$), and f_i ($= u_i - v_i$) have a standardized trivariate normal distribution, with mean vector zero and a covariance matrix with ones along the diagonal and off-diagonal elements $\sigma_{\epsilon e}$, $\sigma_{\epsilon f}$, and σ_{ef}. With all three error variances normalized to unity, we cannot identify the β vector itself, although proportionality across equations can readily be imposed. Results will be in terms of the fitted choice probabilities and the factors which influence them.

The unknown parameters, β_1 (= β/σ_e), β_2 (= β/σ_ϵ), δ_1 (= δ/σ_e), δ_3 (= δ/σ_f), η_3 (= η/σ_f), σ_{ef}, and $\sigma_{\epsilon f}$, can then be estimated by maximizing the likelihood function:

$$(14) \qquad L(\beta_1, \beta_2, \delta_1, \delta_3, \eta_3, \sigma_{ef}, \sigma_{ef}) =$$

$$\prod_{i=1}^{n} \left[\int_{-\infty}^{Z_i\delta_3 - W_i\eta_3} \int_{-\infty}^{X_i\beta_1 + Z_i\delta_1} g(e_i, f_i)\, de_i\, df_i \right]^{T_iY_i}$$

$$\left[\int_{-\infty}^{Z_i\delta_3 - W_i\eta_3} \int_{X_i\beta_1 + Z_i\delta_1}^{+\infty} g(e_i, f_i)\, de_i\, df_i \right]^{T_i(1 - Y_i)}$$

$$\left[\int_{Z_i\delta_3 - W_i\eta_3}^{+\infty} \int_{-\infty}^{X_i\beta_2} g(\epsilon_i, f_i)\, d\epsilon_i\, df_i \right]^{(1 - T_i)Y_i}$$

$$\left[\int_{Z_i\delta_3 - W_i\eta_3}^{+\infty} \int_{X_i\beta_2}^{+\infty} g(\epsilon_i, f_i)\, d\epsilon_i\, df_i \right]^{(1 - T_i)(1 - Y_i)} .$$

where $g(e,f)$ and $g(\epsilon,f)$ signify the bivariate normal density function for the errors in the retrofit and audit equations in cases where audits *did* and *did not* take place, respectively. (See DeGroot (1975, p. 248) for the precise functional form of this joint density.[5])

The likelihood function in equation (14) is the least-restrictive "ideal" specification. However, we will conserve upon parameters by constraining the β vectors to be proportional across the "with" and "without" audit outcomes (i.e. $\beta_2 = \beta_1(\sigma_\epsilon/\sigma_e)$. If self-selection bias is present, the coefficient (δ) on the uncertainty-reduction variable (Z) will be different, implying that the naive model misstates the influence of the audit program on retrofit behavior.

3. Data

We utilize a dataset generously provided by the Los Angeles Department of Water and Power: their *Residential Energy Survey* for 1983. Our estimating sample includes 969 respondents living year-round in resident-owned, single family detached homes. The construction of the variables used for estimation is outlined in the Appendix I and described in much greater detail in supplementary documentation available from the authors.

The "program" participation question on the survey reads: "Have you had a home energy survey of your residence?" The retrofit question asks respondents to indicate whether they added ceiling insulation "last year," "prior to a year ago," "never," or whether they were "not sure." The two positive responses were merged and households responding "not sure" were dropped from the sample.[6]

Table I summarizes the acronyms, means, and standard deviations of the constructed variables used for estimation.

4. A Quadratic Indirect Utility Function with Sociodemographic Shifters

Our basic indirect utility function is quadratic:[7]

$$V = \beta_1 Y + \beta_2 p_h + \beta_3 p_c + \beta_4 Y^2 + \beta_5 p_h^2 + \beta_6 p_c^2 + \beta_7 Y p_h + \beta_8 Y p_c + \beta_9 p_h p_c \quad (15)$$

However, it is the difference between (expected) utility *after* the potential retrofit and (known) utility *without* the retrofit which is presumed to determine retrofit activity:

Table I

Variable Acronyms and Descriptive Statistics
(n = 969; owner-occupied single family dwellings)

Acronym	Description	Mean or Proportion (std.dev.) Unweighted	Weighted
RETRO	household reports having retrofitted with attic insulation	0.6120	0.5732
AUDIT	household reports having had and energy audit	0.2033	0.1946
Y	household income ($ thousand)	39.29 (22.50)	36.66 (22.77)
C	retrofit cost ($ hundred)	1.532 (0.6404)	1.519 (0.6298)
P_h^b	price of heating (pre-retrofit) ($ per HDD)	0.5654 (0.2290)	0.5651 (0.2211)
P_h^a	price of heating (post-retrofit) ($ per HDD)	0.2797 (0.09847)	0.2812 (0.09613)
P_c^b	price of cooling (pre-retrofit) ($ per CDD)	0.7328 (0.6571)	0.5852 (0.6593)
P_c^a	price of cooling (post-retrofit) ($ per CDD)	0.3497 (0.3124)	0.3105 (0.3166)
HSZ	number of people in household	2.894 (1.362)	2.805 (1.389)
DNEW	=1 if occupied house for < 1 year	0.03096	0.02667
SENS	=1 if children or elderly present	0.3860	0.4112
SQFT	square footage of house (hundreds)	17.42 (7.004)	17.14 (6.997)
EDUC	education level of household head (years)	14.50 (2.641)	14.39 (2.762)

$$(16)\qquad \Delta V = V_a - V_b = \beta_0 + \beta_1(Y\text{-}C - Y) + \beta_2(p_h^{\,a} - p_h^{\,b}) + \beta_3(p_c^{\,a} - p_c^{\,b}) + \beta_4(Y\text{-}C - Y)^2 + \beta_5(p_h^{\,a} - p_h^{\,b})^2 + \beta_6(p_c^{\,a} - p_c^{\,b})^2 + \beta_7[(Y\text{-}C)p_h^{\,a} - Y\,p_h^{\,b}] + \beta_8[(Y\text{-}C)p_c^{\,a} - Y\,p_c^{\,b}] + \beta_9(p_h^{\,a}\,p_c^{\,a} - p_h^{\,b}\,p_c^{\,b}).$$

The same parameters appear in ΔV as in V. The intercept term, β_0, can be interpreted as an alternative-specific dummy variable associated with installing a retrofit.

We have allowed the data to suggest which β coefficients in equation (16) are influenced by household-specific variables. Rudimentary specification searches suggest: $\beta_1 = \gamma_1 + \gamma_2\ HSZ_i$, $\beta_2 = \gamma_3 + \gamma_4\ DNEW_i$, and $\beta_4 = \gamma_5 + \gamma_6\ SENS_i$. The number of household members (HSZ) for a given level of total household income will affect the household's decision-making process with respect to the allocation of income. If the household has not yet experienced the full cycle of seasons in this particular house (DNEW = 1), they may not yet fully appreciate the costs of not retrofitting, or may not have had the opportunity to do so. SENS captures differences in temperature variation *tolerance* of different types of households. Those with small children or elderly people present (SENS = 1) tend to keep interior temperatures within a narrower range. Households having only non-aged adults and school age children seem more resilient to temperature variation and also have fewer inactive people around the house during the daytime.

Neglecting selectivity bias, the audit effect would enter a simple probit model for the retrofit decision merely as an additive interaction term: Z = AUDIT*SQFT. With selectivity correction, the full likelihood function in (14) is maximized.

5. <u>Results and Interpretation</u>

a. A Simple Probit Model for the Retrofit Decision :

The first column of part 1 of Table II presents the results for an ordinary probit analysis This model ignores selectivity bias, so we will postpone a detailed discussion of the utility parameter estimates until later. In the meantime, note that despite the multicollinearity among many of the variables, we still achieve statistically significant parameter estimates for most of the parameters of the indirect utility function.[8]

We are primarily interested in the coefficient on the AUDIT*SQFT variable. While the estimated value just misses statistical significance at the 10% level, it seems likely that with slightly richer data for the construction of the variables used in this model, we might easily conclude that audit effects are statistically significant.[9]

b. A Simple Probit Model for the Audit Participation Decision:

Part 2 of Table II describes the audit choice model. The positive and significant coefficient on SQFT suggests that the larger the anticipated benefits from auditing, the greater the probability that an audit will be taken. More education increases the probability of taking an audit, suggesting perhaps that education may lead to greater awareness of audit programs, thus reducing the costs of participation. The income coefficient is not statistically significant, but it does bear the anticipated sign.

But the audit participation model is not without problems. Two of the slope coefficients are strongly significant at the 5% level and a likelihood ratio test easily rejects jointly zero slope coefficients (even at the 0.001 level). However, the model predicts *no* audit activity.[10] It seems that the decision to take an audit might be affected primarily by unmeasurable social

Table II

Weighted Parameter Estimates

(n = 969; single-family, owner-occupied dwellings)

Variable	Ordinary Probit Estimates	MLE Estimates Controlling for Error Correlations
1. RETROFIT DECISION MODEL:		
constant	0.3481 (1.941)	0.3414 (1.483)
(Y-C - Y)	0.8338 (3.223)	0.8373 (2.616)
HSZ * (Y-C - Y)	-0.05062 (-2.704)	-0.05121 (-2.164)
$(p_h{}^a - p_h{}^b)$	-3.390 (-2.066)	-3.392 (-2.057)
DNEW * $(p_h{}^a - p_h{}^b)$	2.268 (2.376)	2.311 (1.826)
$(p_c{}^a - p_c{}^b)$	-0.4877 (-0.9948)	-0.4960 (-1.276)
$(Y-C)^2 - (Y)^2$	-0.0003483 (-0.07928)	-0.0003203 (-0.07169)
SENS * $(Y-C)^2 - (Y)^2$	-0.004712 (-3.966)	-0.004733 (-2.798)
$(p_h{}^a)^2 - (p_h{}^b)^2$	5.183 (2.797)	5.158 (2.990)
$(p_c{}^a)^2 - (p_c{}^b)^2$	0.4465 (0.5959)	0.4161 (0.8277)
$[(Y-C)p_h{}^a - Y\, p_h{}^b]$	-0.03032 (-1.254)	-0.03077 (-1.164)
$[(Y-C)p_c{}^a - Y\, p_c{}^b]$	0.02050 (3.225)	0.02059 (2.914)
$(p_h{}^a\, p_c{}^a - p_h{}^b\, p_c{}^b)$	-1.448 (-1.492)	-1.418 (-1.944)
AUDIT*SQFT	0.009343 (1.631)	0.005136 (0.4052)
Log L at zero	-661.25	-
max Log L	-609.84	-

2. AUDIT DECISION MODEL:		
constant	-1.914 (-6.992)	-1.912 (-6.904)
SQFT	0.01474 (2.015)	0.01460 (1.996)
EDUC	0.05770 (2.860)	0.01460 (2.808)
Y	-0.001286 (-0.5092)	-0.001172 (-0.4595)
log L at zero	-477.60	-
max log L	-468.54	-
3. PARAMETERS FOR JOINT MODEL:		
σ_ϵ(no audit)/σ_e(with audit)	1.0	0.9868 (3.243)
σ_{ef}(with audit)	0.0	0.06205 (0.3472)
$\sigma_{\epsilon f}$(no audit)	0.0	0.0
max log L	-	-1078.30

or psychological variables. Unfortunately, this weakness of our audit model can be expected to handicap any jointly estimated model.[11]

c. *Joint Weighted Probit Model for Retrofit and Audit Decisions:*

Optimization of likelihood function in (14) would ordinarily yield jointly estimated probit parameters for the retrofit and audit decisions plus additional parameters for the ratio of standard deviations, σ_ϵ/σ_e, and for the two error correlations, σ_{ef} and $\sigma_{\epsilon f}$. Unfortunately, $\sigma_{\epsilon f}$ displays a persistent tendency towards -1 with this dataset, even with heavy penalties whenever this value is approached. We suspect that our inability to identify a plausible value for this correlation is an artifact of the poor predictive power of our audit choice model. The joint model relies upon the relative proportions of observations falling into each quadrant of the pertinent half of each bivariate error distribution in equation (14) to infer the degree of correlation between the errors. If the algorithm finds *no* observations in one quadrant, there is no evidence that the correlation differs from -1 or +1, since only the *proportions* of observations in each quadrant are observable.

Our recourse is to estimate a slightly more restrictive model. In separate probit models for both the audit and the retrofit decisions, we are implicitly constraining both σ_{ef} and $\sigma_{\epsilon f}$ to be zero. We can still generalize these models usefully by retaining the assumption that $\sigma_{\epsilon f}$ is zero, but allowing σ_{ef} to be non-zero.[12] These slightly less general models converge readily.[13]

Results for the joint model also appear in Table II. The usual "probit" coefficients (β/σ) are made proportional (across cases where audits were and were not taken) by allowing σ_ϵ/σ_e to differ from unity. While σ_ϵ/σ_e equals 0.9868 when unconstrained, this value is not statistically significantly different from one.[14] And σ_{ef}, when unconstrained, takes on a value of 0.06205--small but positive, although statistically insignificant.[15]

However, we are most concerned about the implications of the selectivity correction process for the estimated coefficient on the AUDIT*SQFT variable, which is interpreted as the "program effect." Simple probit models for the retrofit decision alone imply that this program effect is statistically discernible. But whereas the coefficient is 0.009343 in the simple *quadratic* probit model, it is only 0.005136 in the corresponding jointly estimated model. And this revised estimate comes nowhere near statistical significance. So even with a correlation of less than 0.1 between just *one* of the two pairs of error terms, the naive probit model overstates the effect of the audit on retrofit behavior by almost double.[16]

Researchers and policy makers would be well advised to question the findings of models which ignore potential self-selectivity. And without actually estimating a joint model of retrofit decisions and audit participation decisions, it is difficult to claim that selectivity bias is not present.[17]

6. Simulations: the Practical Implications of the Fitted Models

Our primary interest concerns the different implications of the two estimation procedures for the predicted level of retrofit activity with and without the audit program. Simulations will be based upon our model's within-sample predictions of behavior. We generate a weighted sum of the fitted retrofit choice probabilities over the sample and treat this sum as our predicted number of retrofitting households.

Of the 969 (weighted) households in our sample, 555.38 actually retrofitted. The simple probit model predicts that 556.72 households retrofit. In a counterfactual exercise, we can set AUDIT = 0 for all households. Recomputing the fitted probabilities results in the prediction that 545.65 households retrofit. Without audits, the number of retrofits would have been lower by 11.07, a 1.99% decrease in activity.

In contrast, for the *joint* model, 551.08 households are predicted to retrofit.[18] Artificially removing the audits results in 544.94 households retrofitting (lower by only 6.14, a 1.11% decrease).

But even without corrections for selectivity bias, the discernible effects of energy audit participation on retrofit behavior are very small. Is an audit program necessarily the most effective way to encourage retrofit activity? Table III compares *audit* effects on retrofit decisions with the apparent effects of *other* changes in the consumption environment.

Using the parameters for the jointly estimated model, we first simulate changes in energy prices, retrofit costs, and incomes. A 5% higher relative price of heating fuel increases retrofit activity, implying an "arc elasticity" of retrofit activity with respect to heating fuel prices of 0.6. Arc elasticity with respect to the relative price of electricity (for cooling) is roughly 0.26. Simulated changes in real incomes suggest an elasticity of only 0.12. If retrofit costs are adjusted without altering incomes, however, an arc elasticity of about -0.58 seems to apply.

We can also use simulations to show that the presence of children or elderly persons in some households contributed to roughly 30 of the retrofits which took place. Likewise, if it were not for the 3% of recent movers who have occupied their dwellings for less than a year, retrofit frequency would have been higher by more than five cases.

We can simulate the possible effects on retrofit activity of modest changes in *household* sizes. The arc elasticity is roughly 0.14; increasing household size by 5% results in nearly four more retrofits in our simulations.

Table III

Summary of Simulations

Simulation	Number Retrofitting	Absolute Change	Implied Arc Elasticity
fitted model (actual data)	551.08	-	-
no audit participation	544.94	-6.14	-
5% increase in heating costs	567.96	16.88	0.61
5% increase in cooling costs	558.28	7.20	0.26
5% decrease in retrofit costs	567.10	16.02	-0.58
5% decrease in real income	547.83	-3.25	0.12
5% increase in real income	554.30	3.22	0.12
absence of children and elderly persons (SENS = 0)	520.64	-30.44	-
no recent movers (DNEW = 0)	556.54	5.46	-
5% decrease in household size	547.26	-3.82	0.14
5% increase in household size	554.89	3.81	0.14
5% decrease in house sizes	567.94	16.86	-0.61

* Elasticities computed for 10% changes were the same to within 0.01 in all cases.

The influence of *dwelling* size can be assessed just as easily. SQFT is a multiplicative factor in the calculation of retrofit costs and pre- and post-retrofit heating and cooling prices, as well as the interactive dummy for audit participation. A 5% decrease in house sizes results in 16.86 more retrofits being done, implying an arc elasticity of about -0.6.

All of these simulation results based on the quadratic indirect utility specification seem intuitively plausible.[19] They are limited *ceteris paribus* predictions, but they do provide us with helpful insights regarding the identity and relative influence of factors which affect household energy retrofit activity.

8. Conclusions and Caveats

We have presented an analysis of energy audits as an example of program evaluation when the program in question merely generates information (which reduces the uncertainty associated with households' post-action utility levels). A variety of government programs are of this type (such as aptitude or skills testing programs or worker-job matching services). Participation in these programs is potentially endogenous, and the intended effect of the program is sometimes a discrete outcome, such as a change in employment status (unemployed/employed) or job mobility (move/stay). The youth joblessness addressed by Rees (1986) could be one example. Rather than examining subsequent earnings (as is done by Kiefer (1979)), we might profitably treat "employment or joblessness" as a discrete outcome variable.

We have adapted a suitable theoretical model from the literature on manpower training and earnings effects to the discrete outcome case. The resulting full information maximum likelihood estimation procedure is a useful prototype for other applications. Of course, the endogenous explanatory variable need not be government program participation; other qualitative explanatory variables in many binary choice models may be endogenous. (Consider job mobility as a determinant of migration in Bartel (1979), or marital status as another determinant, in Mincer (1978).)

The dataset available for the audit/retrofit application presented in this paper offers only very sparse information on the types of variables one would ideally require to generate the effective prices of heating and cooling with and without energy retrofits. Still, we find that simple probit models suggest tangible audit program effects, but unobserved characteristics of households apparently make them more likely to retrofit *and* to take an audit. Self-selection into the audit program means that the simple probit model gives the program considerably more credit than it deserves for stimulating retrofit activity.

One caveat: this study addresses only the *direct* effects of the audit program. We cannot assess the externalities generated by the program. A household may be induced to retrofit merely because of *publicity* regarding the audit program, not because it participates itself. However, if these effects are important, it would seem that an intensive general public information campaign might be just as effective as detailed audits conducted for individual households.

We have used our fitted models to simulate other counterfactual states of the world besides the absence of audit programs. It is straightforward to consider the effects on retrofit activity of energy price changes, real income changes, or retrofit subsidy programs. If society perceives that the level of energy conservation retrofit activity is too low, it appears that the manipulation of retrofit costs and heating fuel prices might be the most effective ways to encourage a more socially desirable level of retrofits.

Household-specific information dissemination programs, such as the energy audits considered here, appear to have a less discernible effect on behavior.

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ENDNOTES

[1] Recent summaries and evaluations of techniques used in these models are contained in Heckman and Robb (1985), and Lalonde (1986).

[2] They use essentially a "Heckman two-stage" correction procedure (for a simplified description, see Maddala, 1983).

[3] We must assume that households compensate for the annual baseline number of degree days (i.e. that they maintain a 65 degree indoor temperature).

[4] Refer to Bjorklund and Moffitt (1987) for an outline of a self-selection model in the *continuous* outcome case. To facilitate comparisons, we mimic their notation.

[5] We employ a fast bivariate normal cumulative density "integrator" function called BIV2, attributed to J.A. Hausman.

[6] It is conceivable that the attic insulation might predate the audit, but we must assume that such events are infrequent.

[7] We have also examined translog and generalized Leontief specifications.

[8] Of the 36 unique pairs represented by the nine utility function variables, 20 display correlations in excess of 0.6, 9 have correlations greater than 0.8 and 4 correlations exceed 0.9. Six variables are also strongly correlated with SQFT.

[9] In a translog simple probit model, the coefficient on AUDIT*SQFT has a t-ratio of 1.760; in a generalized Leontief model, the t-ratio is 1.702.

[10] Of the 969 unweighted households, only 178 actually took audits. The maximum fitted probability is 0.36. Extensive specification searching yielded no appreciable improvement.

[11] Nevertheless, a researcher might consider a simple "two-stage" model which partially corrects for error correlations. If fitted probabilities from the audit model are substituted for the audit dummy in the AUDIT*SQFT term in the retrofit model, the resulting coefficient is 0.2365 (with t-ratio 4.7621), suggesting significant audit effects. A more general specification mimics Maddala's (1983, p. 227) equation 8.19, and yields a strongly significant coefficient of 2.481 on the Pr(AUDIT)*SQFT term. While these estimates are consistent, they are inefficient and therefore less reliable than the one-stage model described next.

[12] The other option did not result in any significant progress towards convergence, even after 100 iterations and over 10,000 function evaluations.

[13] Since we are unconstrained by the cost of computing time, we use numerical derivatives.

[14] Since $e = \epsilon + u$, we have $\sigma_e^2 = \sigma_\epsilon^2 + \sigma_u^2 + 2\sigma_{\epsilon u}$. Unless the covariance term is negative and overwhelms σ_u^2, we would expect $\sigma_\epsilon/\sigma_e = 1$.

[15] In the translog specification, the maximized log-likelihood for the joint model is only -1087.59; σ_ϵ/σ_e equals 0.8538 (with t-ratio 2.523) and $\rho_{e\epsilon} =$ 0.06318 (with t-ratio 0.2687). For the generalized Leontief specification convergence beyond an accuracy of 10^{-3} was not attained, despite 122 iterations and over 28,000 function evaluations. We do not consider the

estimates at this stage to be reliable, given the flatness of the likelihood demonstrated in the other two specifications.

[16] Similarly, in the translog specification, the program effect drops from 0.009737 in the simple probit model to 0.004706 in the joint model.

[17] Presumably, it would be possible to devise some Lagrange-Multiplier-type test, but this would be a complex task.

[18] The fit of the retrofit decision portion of the joint model is compromised slightly when we simultaneously estimate the audit choice.

[19] For the translog and generalized Leontief specifications, the same cannot be said. However, neither of these models fits the data as well. Here, the lesser flexibility of the quadratic specification seems advantageous.

APPENDIX I - Variable Construction

Other questions on the survey concern loan programs and tax credits, but it is difficult to quantify the *economic* effects of these measures for particular households. *Awareness* of these programs motivates consumers to retrofit and this awareness is unmeasured. The survey also asks questions about other retrofit measures, but their expected costs and savings depend too much on unreported characteristics of the dwelling.

We delete observations with no data on income, education, number of bedrooms, number of persons in the household, or tenure in their current dwelling. We include only households whose main source of heating fuel is gas or electricity, who knew whether or not they added ceiling insulation, and who knew the approximate year their house was built. We use weights based on sample and population frequencies from cross-tabulations of general location (metro, harbor, or valley) and level of electricity consumption.

For those who did not report square footage, we estimate square footage using a simple regression on the number of bedrooms. Insulation costs are computed from materials costs, labor costs, size of the house, and the use of tax-incentive programs for retrofits. We use estimates from popular literature to assign approximate labor and materials costs. (For attic insulation, we assume a materials cost of $.42 per square foot, and an implicit time cost of installation of $.50 per square foot. For respondents who report taking tax credits, we deduct 35% from the insulating costs; for all others, we are forced to assume poor information about tax credits and to assign the full computed cost.)

To calculate cooling and heating prices, we must approximate R-values, efficiency of fuel use, and fuel prices. We use published average energy prices for gas and electricity in Los Angeles for 1983 and assume that gas efficiency is .55 and electric efficiency is 1.0. We generalize that all houses are common wood-frame structures and employ standard ASHRAE *Handbook of Fundamentals* formulas to determine typical per-square-foot thermal resistance of these materials. We assume that houses built after 1975 have insulation which complies with contemporary building practices or regulations for Southern California. For houses built before 1975, we assume no insulation unless the household indicated that insulation is in place. We use R-values claimed by the household whenever these are available.

Heating and cooling degree-day data are available for nine distinct locations in the Los Angeles area. Using zip codes to identify localities, we assume that heating and cooling degree days equal those of the nearest weather station.

In constructing our variables, we must rely heavily upon variations in square footage to determine measures of retrofit costs and potential energy savings. Compared to some other surveys, the LADWP questionnaire collects only very sparse information about the configuration of each dwelling, and the localized area of the survey precludes reliance on extensive climate variation to generate independent variation in heating and cooling prices.

APPENDIX II - Regularity Conditions

Whenever one employs a utility-theoretic specification, it is routine to examine the fitted indirect utility function for consistency with the regularity conditions required by neoclassical microeconomic theory. The first partial derivatives vary across observations:

$$\partial V/\partial Y = \gamma_1 + \gamma_2 HSZ + \gamma_5 Y + \gamma_6 (Y)(SENS) + \beta_7 p_h + \beta_8 p_c \tag{19}$$

$$\partial V/\partial p_h = \gamma_3 + \gamma_4 DNEW + \beta_5 p_h + \beta_7 Y + \beta_9 p_c$$

$$\partial V/\partial p_c = \beta_3 + \beta_6 p_c + \beta_8 Y + \beta_9 p_h$$

Microeconomic utility theory tells us that we should have $\partial V/\partial Y > 0$, $\partial V/\partial p_h < 0$, and $\partial V/\partial p_c < 0$.

The second derivatives of the indirect utility function are $\partial^2 V/\partial Y^2 = \gamma_5 + \gamma_6 SENS$, $\partial^2 V/\partial {p_h}^2 = \beta_5$, and $\partial^2 V/\partial {p_c}^2 = \beta_6$. (We should have $\partial^2 V/\partial Y^2 < 0$, $\partial^2 V/\partial {p_h}^2 > 0$, and $\partial^2 V/\partial {p_c}^2 > 0$.) The cross-partial derivatives are constant, with $\partial^2 V/\partial Y \partial p_h = \beta_7$, $\partial^2 V/\partial Y \partial p_c = \beta_8$, and $\partial^2 V/\partial p_h \partial p_c = \beta_9$.

Descriptive statistics for the fitted values of the derivatives appear in Table A.

Table A
Compliance with Regularity Conditions

Condition		Before Retrofit		After Retrofit	
		mean	% same sign	mean	% same sign
Monotonicity:	$\partial V/\partial y > 0$	0.6139 (0.1272)	0.9988	0.6199 (0.1245)	0.9988
	$\partial V/\partial p_h < 0$	-2.349 (1.320)	0.9438	-3.333 (0.9123)	1.000
	$\partial V/\partial p_c < 0$	-0.2954 (0.5454)	0.7159	-0.05086 (0.4839)	0.5882
Quasi-convexity:	$\partial^2 V/\partial y^2 < 0$	-0.002242 (0.002387)	1.000	"	
	$\partial^2 V/\partial {p_h}^2 > 0$	5.103 (0.02688)	1.000	"	
	$\partial^2 V/\partial {p_c}^2 > 0$	0.4117 (0.002169)	1.000	"	
Cross-partials:	$\partial^2 V/\partial Y \partial p_h$	-0.03077			
	$\partial^2 V/\partial Y \partial p_c$	0.02059			
	$\partial^2 V/\partial p_h \partial p_c$	-1.418			