Freerider and Freedriver Effects from a High-Efficiency Gas Furnace Program

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ABSTRACT

This paper examines the impacts of energy-efficiency program advertising, product information, and customer incentives on furnace purchasing patterns. Discrete choice methods are used to separate program participants into true participants and freeriders and to separate nonparticipants into true nonparticipants and freedrivers. The model is applied to the furnace portion of Union Gas Limited's Home Equipment Replacement Program. Program rebates have a statistically significant impact on customer choice through their reduction in installed costs, but promotional materials and perceived participation barriers also exert statistically significant influences on furnace choice. The estimated freerider rate is comparable to self-reports, and the estimated freedriver rate is within the bounds given by nonparticipants who were aware of the program.

Historically, freeriders have been considered within most energy-efficiency program cost-effectiveness analyses, while freedrivers have largely been ignored. If only freeriders are included in this case, the furnace program's estimated net-to-gross ratio is 0.21. However, if both freeriders and freedrivers are considered, the net-to-gross ratio rises from 0.21 to 0.75. These results suggest that, if freedrivership does not receive attention comparable to freeridership, the benefits of DSM programs might be significantly understated.

Introduction

Union Gas Limited (Union) introduced its Home Equipment Replacement Program in 1997 to educate customers about energy efficiency, to ease the financial burden of the higher initial costs of high-efficiency equipment, and to help trade allies promote energy-efficient equipment. The program provides literature to customers to show how various furnaces compare in terms of energy-efficiency, support of dealers through joint marketing, and low-interest loans and rebates for the purchase of high-efficiency equipment.

Union evaluated the market effects of the furnace replacement portion of the program in 1998. The primary objective of the study was to determine whether the program's incentives and marketing campaigns changed the share of high-efficiency furnaces in Union's service area and, if so, to determine how the program changed purchasing patterns. More specifically, we sought information on program freeridership and spillover (freedrivership) by identifying and quantifying four categories of furnace purchasers:

- **True Nonparticipants** — customers who purchased a mid-or high-efficiency furnace from non-participating dealers and who were completely unaffected by the program.
- **True Participants** — customers who purchased a high-efficiency unit but would have bought a mid-efficiency furnace without the program and its accompanying incentives.
- **Freeriders** — customers who purchased a high-efficiency model and accepted Union's incentives but would have purchased these units even in the absence of the program.
- **Information Participants (Freedrivers)** — customers who received and used program information to purchase a high-efficiency furnace instead of a mid-efficiency unit but did not apply for program incentives.

We applied discrete choice modeling techniques to separate customers across these categories. A discrete choice model refers to a situation where the dependent variable is discrete rather than continuous. Classic examples from the utility industry include the decision to participate or not participate in an energy-efficiency program; whether to buy a gas, electric, or oil-using piece of equipment; and whether to buy low-, mid-, or high-efficiency equipment. All of these situations share the feature that the outcome is limited to a few discrete choices. Standard regression procedures are not appropriate methods to isolate the influence of choice-specific and demographic attributes on customers' selection from the choice set, so statisticians developed discrete choice methods for this purpose. Greene (1997) and Train (1986) provide detailed descriptions of these modeling techniques, and Train (1995) shows how the methodology can be used to isolate freerider and customer spillover effects from energy efficiency programs.

The multivariate discrete choice modeling approach used here, nested multinomial logit (NML), recognizes that the decisions to participate in Union's program and to buy a mid- or high-efficiency furnace are interrelated. In this framework each customer has three choices:

1. Buy a mid-efficiency furnace
2. Buy a high-efficiency furnace without participating in the program
3. Buy a high-efficiency furnace through the program

After estimating the model, "what if" scenarios are generated by the model coefficients to yield an "inferred baseline." High- and mid-efficiency shares are calculated for cases where there are no program financial incentives and no program information or marketing. Comparison of the shares from these scenarios yields freerider and freedrivership estimates.

A mapping between observed actions, the four categories of furnace purchasers, and the inferred baseline is shown in Figure 1. The NML model is applied to the three observed actions on the left side of the figure. Customers who purchase a mid-efficiency furnace with the program would do so without program incentives and advertising, and are true nonparticipants. Customers who purchased a high-efficiency unit without participating are either true nonparticipants or freedrivers. Those in the latter category would have bought a mid-efficiency furnace in the absence of the program, and as information participants they represent customer spillover effects from the program.

Customers who buy high-efficiency furnaces and accept rebates are also mapped into two categories. They are either true participants who would have purchased mid-efficiency units in the absence of the program or they are freeriders who would have purchased high-efficiency furnaces anyway.

Researchers have applied NML techniques to other utility programs to estimate freerider and spillover effects. Paquette, Train, and Buller (1994) find little evidence of freedrivership spillover effects from a commercial lighting program, but Train and Paquette (1995) find evidence that commercial lighting program advertising influences nonparticipant purchases. Both studies find statistically significant freerider rates.

As these authors note, discrete choice methods cannot estimate all types of program spillover. It can be used to determine the influence of information and advertising on purchase decisions and resulting freedrivership rates. Other approaches must be used to capture program spillover effects on supply — manufacturers, distributors, equipment vendors, builders, etc. For example, one can apply direct elicitation methods and ask these market actors how the program has influenced their behavior, or one can combine direct elicitation and the Analytical Hierarchy Process (AHP) in a hybrid qualitative-quantitative evaluation of supply-side market effects. See Haeri, Khawaja, and Stout (1997) for more information on these approaches.

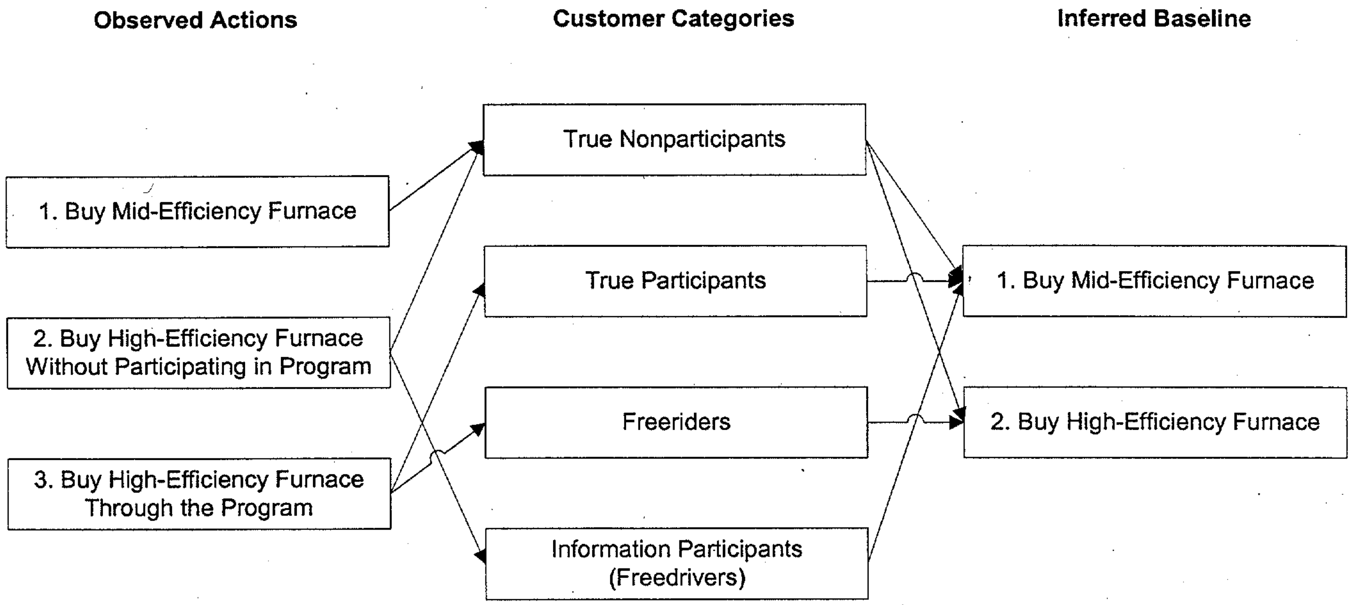

Figure 1. Customer Actions and Categories

Data Development

Union Gas conducted a telephone survey of 800 residential customers to collect the following types of information from program participants and furnace purchasers who did not participate in the program:

- For nonparticipants, whether the customer purchased a mid- or high-efficiency furnace (this information was known for program participants)
- Customer demographic variables (income, age, education, family size, home ownership, previous program participation)
- Dwelling characteristics (square footage, type of residence)
- Customer awareness of energy-efficiency information and the source of this information (bill inserts, newspaper ads, other program literature) and attitudes toward energy-efficiency (perceptions of program participation barriers, importance of energy-efficiency, expectations of future energy price increases, perceptions of "comfort" with energy-efficient equipment)
- Furnace capital costs

Several steps were required to enable this information for inclusion in the discrete choice model, including:

- Creation of index for attitudinal questions relating to the difficulty of finding a contractor.
- Development of a program 'awareness' variable to reflect whether the customer relied on bill inserts, newspaper ads, or program literature prior to purchasing a furnace.
- Replacement of missing data from certain questions (e.g., income, age) with the sample means to allow all respondents to remain in the analysis.

We initially performed simple cross-tabulations and other bivariate analyses relating various customer attributes and responses to program participation and furnace efficiency choice decisions. These partial analyses provided insights into whether a variable should be considered for inclusion in the multivariate discrete choice models.

Chi-square tests of differences between groups revealed statistically significant differences in certain housing characteristics by efficiency levels and participation. Customers who live in smaller homes (less than 1,500 square feet) were more likely to buy mid-efficiency furnaces, while customers in larger homes (greater than 1,500 square feet) were more likely to purchase high-efficiency models. Customers in newer homes (less than 10 years) were also more likely to buy a high-efficiency, but those in brand new homes were unlikely to do so through the program. This is not surprising since there are different furnace delivery channels and long standing contractor-dealer relationships in new construction. As there were only 38 new homes in the sample, this portion of the sample was too small to separately analyze the new construction furnace market. We therefore excluded new homes from the final sample, leaving 762 customers for the NML analysis.

The presence of a chimney is another key factor that distinguishes efficiency levels. Customers without a chimney were more likely to purchase a high-efficiency furnace. Those customers who converted from electricity to gas were also more likely to buy high-efficiency models and participate in the program. Nonparticipants found it more difficult to find a program-certified contractor, and there were no significant differences across groups in demographic variables.

We also found differences in terms of the information sources relied upon by high-efficiency participants and nonparticipants. Participants were more likely to have seen one or more of the many information sources provided by the program: bill inserts, news ads, Wise Energy Use Guide, Get the Most From Your Heating System Guide, and the Home Energy Advisor. More than 90% of high-efficiency program participants used one or more of these sources for energy-efficiency information, while nearly 80% of high-efficiency non-participants did not use a single one of these sources to obtain information.

NML Methodology

The NML model is depicted in Figure 2. The model assumes that unknown factors influencing the purchase of a high-efficiency furnace as a program participant or nonparticipant are correlated, so these alternatives are placed in the same "nest." The mid-efficiency alternative occupies its own nest.

The NML model attempts to describe each customer's "utility" or value of the three alternatives. In this framework, each of the 762 customers chooses one of the three alternatives, so the number of customers is multiplied by three to yield a total of 2,286 observations. The algorithm estimates the probability that the customer will choose each alternative, including the one actually chosen. Predicted market shares are given by averaging the probabilities over all customers.

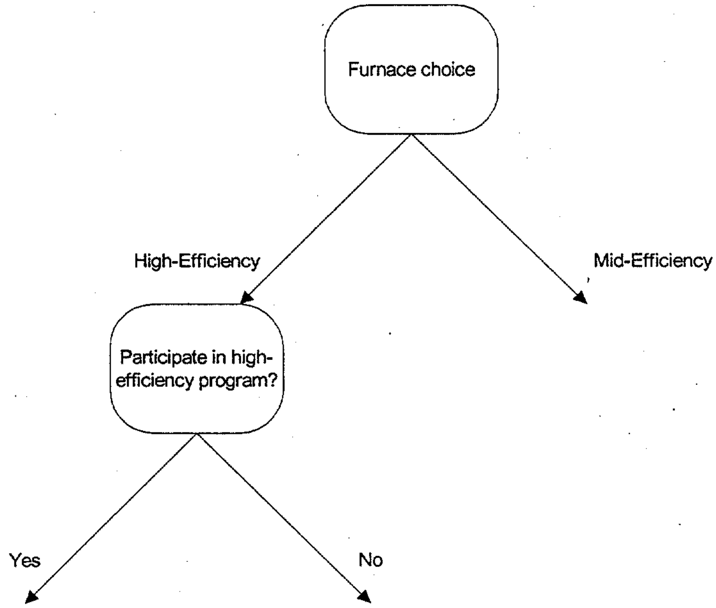

Figure 2. Nested Multinomial Logit (NML) Framework

We used NLOGIT, a full information maximum likelihood estimator, to perform the analysis. NLOGIT is available in LIMDEP, an econometrics software package specifically designed for discrete choice analysis. The model structure is as follows:

1. Choices = MID,HIGHNONP, HIGHPART
2. Tree structure = MIDEFF(MID), HIGHEFF(HIGHNONP, HIGHPART)
3. Customer satisfaction attributes:
   U (MID) = ALTM + a1* INSTCOST
   U (HIGHNONP) = ALTN + a2 * FINDNONP + a1 * INSTCOST
   U (HIGHPART) = a3 *AWAREH + a1 * INSTCOST
4. Branch choice equation:
   U (MIDEFF, HIGHEFF) = b1* CHIMMID + b2 * ELECMID + b3 * SQFTMID

where

- MID is the mid-efficiency furnace alternative
- HIGHNONP is the high-efficiency furnace, nonparticipant alternative
- HIGHPART is the high-efficiency furnace, participant alternative
- ALTM is an alternative-specific constant for the mid-efficiency furnace (equal to 1 for the mid-efficiency alternative and zero for the other alternatives)
- ALTN is an alternative-specific constant for the high-efficiency, nonparticipant alternative
- INSTCOST is the installed cost for each alternative, which varies by furnace type for each household. Differences between INSTCOST for the two high-efficiency alternatives reflect the value of program incentives.
- FINDNONP is an index that captures the customer's perceived difficulty of finding a Union-qualified furnace contractor and is interacted with the HIGHNONP alternative.

- AWAREH is equal to program awareness interacted with the HIGHPART alternative (program awareness equals 1 if the customer relied on Union's program information to help make the purchase decision, and zero otherwise)
- CHIMMID is equal to the presence of a chimney interacted with MID
- ELECMID is equal to 1 if the customer converted from electricity and is interacted with MID
- SQFTMID is equal to dwelling square feet interacted with MID

Since the original sample of customers is based on the choices customers made rather than a simple random sample, this model was "weighted" in estimation to reflect population weights.

NML Results

NML model results are summarized in Table 1. The table includes coefficient estimates, standard errors, and the probability that each coefficient is not significantly different from zero. Two sets of parameters are provided:

1. Customer utility attributes for the three alternatives
2. Branch choice attributes for the MID versus HIGHEFF choice

All of the customer satisfaction function attributes are consistent with our notions of customer purchasing behavior; model coefficients are the right sign and are statistically significant. The negative coefficient on INSTCOST indicates that the higher installation costs are for a given alternative, the less value it provides. The positive coefficient on FINDNONP means that the greater the customer's perceived difficulty of finding a Union-qualified furnace contractor, the greater the value of the HIGHNONP alternative. Similarly, the positive coefficient on AWAREH indicates that awareness of program advertising and information made the HIGHPART alternative more attractive. The positive coefficients on ALTM and ALTN indicates that there are other factors that made the MID and HIGHNONP alternatives valuable relative to the HIGHPART alternative, all other things equal. Note that conclusions about the relative magnitude of these coefficients can be misleading. For example, INSTCOST ranges from about $1,000 to $5,000, and if were scaled to range from $1 to $5 (in thousands) its coefficient would be -6.1.

Table 1. Full Information Maximum Likelihood Estimates

Variable	Coefficient	Standard Error	Prob > z
Customer Satisfaction Attributes			
ALTM	2.2915	0.4258	0.0000
INSTCOST	-0.0061	0.0011	0.0000
ALTN	3.9233	0.3919	0.0000
FINDNONP	0.0483	0.0208	0.0203
AWAREH	2.7541	0.3130	0.0000
Branch Choice Attributes			
CHIMMID	1.3797	0.3003	0.0000
ELECMID	-1.3742	0.2398	0.0000
SQFTMID	-0.3831	0.0823	0.0000
Inclusive Value	0.8114	0.0880	0.0000
Restricted log likelihood	-785.3358		
Log likelihood function	-640.6430		
Chi-square	289.3856		0.0000

The branch choice attribute coefficients are also consistent with the expectations based on the bivariate analyses discussed above. Mid-efficiency furnaces provide greater value when a chimney is present, less value if the customer converted from electricity, and less value when dwelling square footage rises.

The inclusive value parameter of 0.81 reflects the degree of similarity across the two high-efficiency options. Since this coefficient is significantly different from zero, the hypothesis of no correlation, which would imply no need for a nested structure, can be rejected. The overall validity of the NML model is estimated by comparing the difference between the log likelihood function to that of a model where all of the coefficients are restricted to zero. This difference is multiplied by 2.0 to yield the chi-square test statistic of 289.39, which exceeds the critical value of 23.59 for nine model parameters at the 0.005 level.

Another, perhaps more meaningful, way to determine whether the NML results are reasonable is to compare the average probability estimates from the model to the populations shares. As shown in Table 2, the NML shares are very similar to the actual shares.

Table 2. Comparison of Actual Market Shares to Estimated Market Shares

	Actual Market Share	Estimated Market Share
MID	36.5%	37.9%
HIGHNONP	49.5%	44.6%
HIGHPART	14.0%	17.5%
MIDEFF	36.5%	37.9%
HIGHEFF	63.5%	62.1%

Freeridership and Freedrivership Effects

The market effects from Union's program can be determined by changing the values of the choice attributes in the NML model in "what if" scenarios. This is accomplished by eliminating the incentive and other parts of the program and viewing the impacts of these changes on the market shares. If the Union Gas program is positively influencing the high-efficiency furnace market share, the high-efficiency share will fall as program features such as incentives and advertising are effectively "removed." Note that this is not accomplished by self-reports from the survey. Rather, we apply the NML model coefficients to hypothetical changes in their associated variables to develop the what-if scenarios. The analysis relies on three distinct scenarios:

1. **Program Case**: This scenario reflects the estimated market shares from the NML model described in the last section.
2. **No Incentive Case**: This scenario makes one change to the program case. For each customer, INSTCOST for the HIGHPART alternative is set equal to INSTCOST for the HIGHNONP alternative. This effectively sets program financial incentives to zero.
3. **No Program Case**: Starting from the no incentive case, the values of the program awareness (AWAREH) and difficulty of finding a contractor (FINDNONP) dummy variables are set equal to zero. Additionally, the HIGHPART alternative is eliminated as an alternative. This scenario can be viewed as the "inferred baseline."

The market shares from each of these scenarios are displayed in Table 3. The MIDEFF share rises from 38.0% to 41.7% if incentives are set equal to zero, and rises to 48.5% if efficiency information and all other program components are eliminated (AWAREH and FINDNONP are set equal to zero). Similarly, the HIGHEFF share falls from 62.0% to 58.3% if incentives are set to zero, and falls to 51.5% if all other program components are eliminated. Therefore, approximately 65% (6.8% ÷ 10.5%) of the overall change in the high-efficiency share was caused by non-incentive program attributes (AWAREH and FINDNONP).

Table 3. What-If Scenarios

	Program Case	No Incentive Case	No Program Case
MID	38.0%	41.7%	48.5%
HIGHNONP	44.6%	51.6%	51.5%
HIGH PART	17.5%	6.7%	NA
MIDEFF	38.0%	41.7%	48.5%
HIGHEFF	62.0%	58.3%	51.5%

The estimated freerider and freedriver rates are then combined with program participant and nonparticipant population figures to determine the net market effects of the program. The results of these calculations are shown in Table 4.

To determine the freerider rate, we first determined the share of HIGHPART customers who were induced to purchase furnaces by program incentives. As the overall high-efficiency share difference attributed to incentives is 3.7% (62.0 – 58.3), the share of HIGHPART customers induced by the program is 21% (3.7 ÷ 17.5). All other HIGHPART customers were freeriders, or 79% of participants. This estimate is identical to the 79% freerider estimate from customer self-reports from the survey, where customers were asked if they would have paid the incremental costs for a high-efficiency unit.

The freedriver rate is similarly calculated. The change in the overall HIGHEFF share from program advertising and other information is 6.8% (58.3 – 51.5). Therefore, the share of HIGHNONP customers influenced by these program features is 15% (6.8 ÷ 44.6). This estimate is within the potential freedrivership upper limit of 20% given by the share of nonparticipating high-efficiency purchasers who reported that they were aware of the program. Customers were deemed aware if they relied at all on program informational materials or advertising prior to selecting a furnace.

Table 4. Net Market Effects of the High-Efficiency Furnace Program

Calculation 1*	Population Estimate	Actual Population Share	Free Riders	Information Participants & True Participants
* Net impacts based on freerider and freedriver rates				
MID	26,422	36.5%		
HIGHNONP	35,876	49.6%		5,497
HIGHPART	10,105	14.0%	7,959	2,146
Net Program Impact				7,643

Calculation 2**	HIGHEFF Population Estimate	NML Population Share Estimates	Market Effects
** Net impacts based on determining HIGHEFF population across scenarios			
Program	44,923	62.0%	
No Incentive	42,237	58.3%	2,686
No Program	37,292	51.5%	4,945
Net Program Impact			7,631

The upper part of Table 4 uses the population associated with each alternative, and the estimated freedriver and freerider rates, to calculate information participants and true participants. Note that the population shares in the third column correspond to actual shares rather than the average probability estimates from the NML model results. The HIGHPART population is multiplied by the freerider rate of 79% to yield freeriders, and the remaining customers in this group are true participants. Information participants are given by multiplying the HIGHNONP population by the freedriver rate of 15%. True participants and information participants are then added together to obtain the net program or market effect, which in this case is over 7,600 high-efficiency furnace purchasers. Dividing this estimate by the total HIGHPART population of 10,105 yields a net-to-gross ratio of 75%.

The lower part of Table 4 presents an alternative calculation of net market effects based on a more direct interpretation of the NML results and scenarios. The total HIGHEFF share for each NML scenario is multiplied by the estimate of the total number of furnaces purchased in Union's service area, 72,403. This yields the respective high-efficiency population estimates. Net market effects are given by the changes in the population across scenarios. High-efficiency furnace purchases fall by nearly 2,700 without incentives, and the number of high-efficiency units falls by an additional 4,900 if the program does not exist. The net-to-gross ratio (which again equals 75%) is given by dividing the total number of high-efficiency furnaces induced by the program (which again exceeds 7,600) by the HIGHPART program population figure of 10,105.

Conclusions

This paper illustrates how discrete choice methods can be used to quantify the relative size of freeriders and information participants. The approach uses model parameter estimates to create "what if" scenarios that are dependent on removing program components, and ultimately creates an inferred baseline.

The estimated freerider rate of 79% is identical to self-reports, and the estimated freedriver rate of 15% is within the 20% bound given by high-efficiency non-participants who are aware of one or more of the program's promotional materials.

As nearly four high-efficiency furnaces are purchased outside the program for every high-efficiency program participant, freedrivership has a strong influence on program cost-effectiveness. Two separate calculation methods suggest that the overall net-to-gross ratio is 75%. This means that, for each high-efficiency participant, Union can take credit for 75% of expected energy savings.

The results of this study also suggest that consideration of freeriders without information participants would severely understate the cost-effectiveness of Union's energy-efficiency initiatives. In this instance, the net-to-gross ratio would be 21% if information participants were not considered in the calculations.

In addition to quantifying freeriders and freedrivers, this methodology can help improve energy-efficiency program design. For example, the results indicate that the effects of program marketing and information on furnace efficiency choice are approximately twice that of incentives. Program attribute rankings in terms of net benefits can by estimated by comparing these effects to the their respective costs. Similarly, one can disaggregate the components of the awareness variable — bill inserts, advertising, and other program literature — to determine the relative effectiveness of various program information channels on market behavior.

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