# Mutual Exclusivity and Rank Ordering of Interactive DSM Measures

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The study develops an algorithm which incorporates relevant economic and demographic variables to determine the loading order of interactive demand-side management (DSM) measures and the proportional share of mutually exclusive DSM measures. The study defines interactive measures as complements and mutually exclusive measures as substitutes. An interactive measure, therefore affects another measure's impact on an end-use load, and a mutually exclusive measure does not. Interactive and mutually exclusive measures need to be distinguished and their impacts analyzed in the context of forecasting models to eliminate potential double counting of impacts in applications where multiple DSM technology options exist.

A two-stage discrete choice econometric estimation technique is used to estimate the probability of adoption and the loading order of the interactive measures. Stage 1 estimates adoption of each measure independent of other measures. The probability of measure adoption is specified as a function of variables that describe the measure and program participants, e.g. rebate amount and dwelling type. Stage 2 estimates the probability that a consumer adopts one measure conditional on the adoption of another measure in the first stage, i.e. the predicted probabilities of adoption in the first stage are used as explanatory variables in the second stage. Goodness-of-fit tests are performed to select models that best reveal the loading order of the measures. For mutually exclusive measures, the probability of adopting each measure is estimated. The sum of the means of the predicted probabilities are normalized to one to determine the shares of the mutually exclusive measures.

## Introduction

The objective of this study is to provide information regarding the probability of adopting mutually exclusive DSM measures and the loading order of interactive demand-side management (DSM) measures by customers participating in both a residential retrofit and rebate program and a commercial/industrial/agricultural retrofit and rebate program instituted by Southern California Edison (Edison). The proportional shares of the mutually exclusive measures and the loading order of the interactive measures as discerned from this study are designed to be used as inputs into long-run DSM forecasting. The study develops empirically based methods to account for overlap between mutually exclusive measures and interactive measures in long-run DSM forecasting. This overlap can cause multiple counting of energy consumption and demand impacts in assessing the potential of DSM resources.

Since participant behavior regarding interactive measures has been known to deviate from adopting certain measures based solely upon levelized costs, this study proposes a procedure to incorporate other relevant variables to capture more completely the decision-making process of the consumer. In addition, mutually exclusive measures are clearly not proportioned equally in the marketplace as often assumed when estimating DSM impacts and forecasting DSM potential. This study also proposes a method to allocate these measures on a more supportable basis.

The study is structured as follows. Initially, a description of the data and the sampling design is provided. Based on the available data and sampling design, the methodology used for estimation is outlined. Finally, the empirical results, recommendations for future research, and concluding remarks are presented.

## Data Description and Sampling Design

### Residential Programs

Data from the Edison retrofit and rebate program database were used to estimate the loading order and proportional share of interactive and mutually exclusive measures, respectively. Three years of recent data were assessed: 1990-1992. A stratified random sample of 5,376 observations was drawn from the database containing 112,392 observations. There were three stratifying variables: dwelling type, climate zone, and whether or not the measure implemented was a refrigerator. The sample was stratified by the measure type since there were only seven measures eligible under the Edison retrofit and rebate program. Of the seven, three of them were refrigerators with different efficiency ratings. The remaining four measures eligible under the program were: heat pumps; centralized air conditioners; through the wall heat pumps; and evaporative coolers. As a result of the three stratifying variables there were 56 strata. Originally, there were to be 96 observations in each cell totalling the sample size of 5,376. However, some strata eventually had more observations than others since certain strata did not have 96 observations in the population. Thus, if there were less than 96 per stratum the remaining observations were reallocated to other strata according to a technique outlined in Cochrane (1977). The total sample size remained at 5,376.

96 observations were chosen in order to obtain a sample with a 95 percent confidence level and a 5 percent margin for error. Thus, the formula used for sampling was:

$$n=\frac{(s_h)^2}{(d/t)^2}. \tag{1}$$

$s_h^2$ is the variance within stratum h, t is the student t statistic corresponding to a 5 percent significance level, and d is the corresponding margin for error of 5 percent. Given that the initial stratifying variables were discrete binary variables taking on values of 0 or 1, the highest that the variance could possibly be was .25 (.5*.5), thus this value was used. Initially, there were four strata; two for the type of dwelling (single family or multi-family) and two for whether the measure was a refrigerator or not. Thus, the sample size was n=384 divided by 4 strata which implies that there are 96 observations within each strata. It was later decided that additional climate zone variables were needed, yet we wanted to preserve the sample size since estimation requiring the use of asymptotic properties is used (as outlined in the Empirical Results section), so 96 observations were chosen for each strata. At minimum we have drawn a sample with a 95 percent confidence level and a 5 percent margin for error. Since it was essentially costless to draw the additional observations we thought it best to incorporate them.

The following variables representing program characteristics were used in the econometric estimation: Dwelling type (single family or multi-family); Levelized cost (G/kWh); Rebate amount ($); Cooling system type (an indicator variable for electric or other); and Climate zone (an indicator variable for the consumer's climate zone, Edison climate zones were used).

### Commercial/industrial/Agricultural Programs

Data from the Edison commercial/industrial/agricultural retrofit and rebate program were used in the analysis. The commercial retrofit and rebate program database was somewhat smaller than the residential retrofit and rebate database although more measures were applicable under the commercial program. A stratified sample of 4,608 observations was drawn from a population of 47,310. The stratifying variable was building type of which there were thirteen. The building types are listed below in the Empirical Results section, however it should be noted that small and large offices were categorized together since the variable for square footage in the commercial program database was at times incomplete. Thus, thirteen, instead of the typical fourteen building types were used. S.I.C. codes were used to determine building type.

The measures applicable under the commercial program were divided into three categories: Space Conditioning, Lighting, and Other. Space Conditioning measures are solely discussed in this paper. The variables that were used in estimation were: building type; kW Reduced; kWh Saved; Levelized Cost (¢/kWh); and Rebate Amount ($).

## Methodology

The following is a description of the methodology utilized to analyze data gathered from Edison.

### Interactive DSM Measures

A discrete choice estimation technique is used to estimate the probability of adoption and the loading order of the interactive programs. The method can be divided into two stages. Stage 1 involves estimating the probability of a consumer (residence or firm) adopting each DSM measure independent of the other available DSM measures. This would be an estimate of a consumer adopting a particular measure first, before another interactive measure is adopted. A binomial Probit model is used to estimate the probability that a consumer would choose to adopt or not adopt a particular measure. The probability of adopting the particular measure would be a function of the demographic characteristics of the participants and the characteristics of the particular measure.

The second stage of the estimation technique involves determining the probability that a consumer adopts one measure conditional on the fact that she has adopted another measure in the first stage. For example, a second stage model would estimate the probability that the participant would adopt an energy efficient water heater given that she adopted the horizontal axis clothes washer in stage 1. In contrast, the opposite model would also be estimated in which the probability that the participant would adopt the horizontal axis clothes washer conditional on the probability of adopting the energy efficient water heater in stage 1.

The models are estimated using the SAS PROBIT procedure. The models are then compared by means of a goodness-of-fit diagnostic test, the Akaike information criterion (AIC). The AIC is a useful diagnostic since it essentially adjusts for differences in the number of coefficients across models (similar to an adjusted $R^2$). The models that perform most successfully given the above criteria will determine the loading order of interactive measures. For example, if the model characterizing the probability of adopting the energy efficient water heater (conditional on the adoption of the efficient clothes washer) fits "best" given the criteria, then that estimated probability would be used to determine the loading order. Once the models have been selected, the ranking of measures will be ordered in terms of the highest estimated probability.

***Model Specification.*** Binomial Probit probabilities will be estimated in both stages described above. The underlying assumption of the Probit model is that consumers are optimizing a utility function, $U_{in}$, comprised of an observed portion of the utility, $V_{in}$, derived from adopting the measure, and an unobserved portion, $e_{in}$. The representative utility for consumer n for alternative i is specified as:

$$U_{i,n} = V_{i,n} + e_{i,n} \tag{2}$$

where the observed and estimable portion of the utility function is:

$$V_{i,n} = \beta\,\omega(Z_{i,n}, s_n). \tag{3}$$

ß is the vector of parameters that is estimated with the Probit technique, $Z_{in}$ are the characteristics of the alternative i as faced by the consumer, and $s_n$ are the demographic variables relating to consumer n. When analyzing the probability of adopting the energy conservation measures, $Z_n$ will consist of the levelized cost of the device, kWh saved by the measure, kW reduced by the measure, and the rebate amount. $s_n$ will consist of the building type (as determined through the SIC codes) of the commercial enterprise. In the model described for stage 2, $Z_{in}$ will contain an instrumental variable(s) that represents the estimated probability of an alternative(s) that was hypothesized to be interactive with alternative i. For example, if we were estimating a stage 2 model for the probability of adopting an Economizer, the estimated probability, $P_j$, of the consumer having adopted an indirect evaporative cooler (derived from a stage 1 binomial Probit model) would be incorporated as an instrumental variable in the variable set, $Z_{in}$. We can therefore estimate the probability of adopting alternative i given that we know the consumer adopted alternative j in time period 1 (stage 1).

Given the assumption about the unobserved portion of the utility and the above specification in (2), the probability that consumer n will choose alternative i is the integral from negative infinity to $e_{in}+V_{in}$ of the normal density function for any given value of $e_{in}$ over all possible values of $e_{in}$ (see (Train 1986) for detailed theoretical derivation of Probit estimation techniques).

## Mutually Exclusive DSM Measures

The techniques for estimating the adoption of mutually exclusive DSM programs are more straight forward than the interactive technique described above. Binary Probit is used to estimate the probabilities of adoption. The type of probabilities described as stage 1 probabilities in the discussion above regarding interactive measures are estimated for the mutually exclusive measures.

The probabilities of adoption are translated into shares for mutually exclusive measures by first estimating a trajectory of predicted probabilities for the binary Probit case for each measure. Next, the mean predicted probability is computed for each measure. For each group of mutually exclusive measures the mean predicted probabilities of each in the group are normalized such that their sum is 1. The normalized mean predicted probability for each measure in the mutually exclusive group is then used as the proportional share of that particular mutually exclusive measure. In this way, the mutually exclusive measure that is most likely to be adopted (has the highest average probability of being adopted based upon the estimation results) would receive the highest proportional share.

## Empirical Results

The following discussion outlines the empirical results of the Probit models used to estimate the probability of implementing/adopting DSM measures. The outline of this section is as follows. Initially, results for the mutually exclusive Residential DSM measures will be discussed. Rankings of the interactive Commercial/Industrial Space Conditioning measures are discussed next. The Probit results for these models will be compared with the levelized costs when ranking the interactive measures. The study concludes with some final remarks and recommendations for future research.

Note, often levelized costs are used to rank interactive measures, yet the technology shares for the mutually exclusive measures are often proportioned equally. In the following sections, we compare the ranking of the interactive space conditioning measures with the ranking determined by the Probit estimation. Also, for mutually exclusive residential measures, we compare the technology shares determined using the Probit technique with the popular technique of allocating each mutually exclusive measure equal technology shares.

The criteria by which the Probit models are evaluated are the Akaike Information Criterion (AIC), which essentially is a means to compare model fit across models, and the P values of estimated coefficients. The computational formula for the AIC is simply: -(Log Likelihood Value of the Estimated Model) + Number of Coefficients Used in the Model (including the intercept). Since the Log Likelihood is typically negative and typically we want to maximize its value in estimation, it makes intuitive sense that we would want to minimize the AIC (i.e., the model with the smallest AIC is chosen). The number of coefficients is incorporated into the AIC in a similar fashion to the commonly used Adjusted $R^2$ in regression. The P value is also used to evaluate explanatory success within a chosen model. The P value reflects the value at which the estimated coefficient is significant. Thus, a low P value is desirable.

In conjunction with the P values which describe the significance level of the coefficients, the $X^2$ statistic is used rather than the student t statistic as a measure of coefficient significance as is appropriate with Probit models.

### Residential DSM Measures

There were a total of seven energy conservation measures that were eligible for rebate under the residential retrofit and rebate program as discussed above: centralized air conditioners, evaporative coolers, heat pumps, three types of refrigerators, and through-the-wall heat pumps. The three types of refrigerators were determined to be mutually exclusive among themselves. In addition, centralized air conditioners, heat pumps, and through-the-wall heat pumps were also determined to be mutually exclusive among themselves. In the case of refrigerators, a consumer would choose to adopt one of the three types of refrigerators since they are substitutes. Also, the consumer would choose to adopt one type of space conditioning measure among the three. We examine refrigerators to illustrate the Probit technique of allocating mutually exclusive measures.

The average probabilities of adopting each of the mutually exclusive measures and the loading order of the interactive measures were estimated using the Probit technique described above. The Probit results are compared to the method of allocating equal shares for mutually exclusive measures.

***Mutually Exclusive Measures.*** The three refrigerators eligible for rebate under the residential retrofit and rebate program varied by the degree of efficiency, level of the rebate, and cost. Refrigerator "1" was the least efficient refrigerator, Refrigerator "2" was the next efficient, and Refrigerator "3" was the most efficient. The means of the predicted probabilities of implementing the three refrigerators based on the Probit results were: .34 (Refrigerator 1), .67 (Refrigerator 3), and .79 (Refrigerator 2). Weighting the Probit results by their stratum weights and normalizing to equal 1 reveals that the proportional shares of the three refrigerators are: .20 (Refrigerator 1), .33 (Refrigerator 2), and .47 (Refrigerator 3). This implies that the highest probability of adoption, based on the weighted and normalized mean of the estimated results, is assigned to Refrigerator 3 which is the most efficient refrigerator. The data also reveal that as efficiency increases the levelized cost of the refrigerator increases. For comparison purposes, if solely levelized costs were used to determine the proportional share of the refrigerators, Refrigerator 1 would have the highest probability of adoption. In sum, the Probit results reveal that consumers prefer the refrigerator with the highest ratio of rebate to cost, Refrigerator 3. Given that Refrigerator 3 is also the most efficient, it benefits a utility to provide a higher rebate/cost ratio for the more efficient DSM technologies since consumers can be prompted to make the investment.

Tables 1-3 reveal the Probit estimation results as outlined in the theoretical section above.

Table 1 reveals that levelized cost, rebate amount, and the type of cooling system (electric or other) have the largest impact on the adoption of Refrigerator 1. Note, the levelized cost variable (LC) in this model is the most significant, according to the $X^2$ (ratio of the square of two

**Table 1.** Probit Results - Refrigerator "1"

| Independent Variables | Coeff. Estimate | Standard Err. | $X^2$ | P Value |
|---|---|---|---|---|
| Intercept | 3.7422 | .9410 | 15.81 | .0001 |
| Dwelling | .8868 | .4993 | 3.15 | .0757 |
| LC | -.3829 | .0433 | 78.18 | .0001 |
| Rebate | .03679 | .0053 | 47.93 | .0001 |
| Cooling Sys. | -1.2382 | .3695 | 11.24 | .0008 |
| Climate | -1.4101 | .8681 | 2.64 | .1043 |
| AIC | 238.89 | | | |

**Table 2.** Probit Results - Refrigerator "2"

| Independent Variables | Coeff. Estimate | Standard Err. | $X^2$ | P Value |
|---|---|---|---|---|
| Intercept | -.2006 | .0938 | 4.57 | .0324 |
| Dwelling | .0262 | .0448 | .34 | .5587 |
| LC | -.0821 | .0169 | 23.57 | .0001 |
| Rebate | .0167 | .0015 | 129.87 | .0001 |
| Climate | -.1325 | .0690 | 3.69 | .0549 |
| AIC | 211.35 | | | |

**Table 3.** Probit Results - Refrigerator "3"

| Independent Variables | Coeff. Estimate | Standard Err. | $X^2$ | P Value |
|---|---|---|---|---|
| Intercept | .3048 | .1002 | 9.26 | .0023 |
| Dwelling | -.3380 | .0588 | 33.07 | .0001 |
| LC | -.0163 | .008 | 4.12 | .0423 |
| Rebate | .00052 | .00017 | 9.21 | .0024 |
| Climate | .3725 | .0879 | 17.96 | .0001 |
| AIC | 287.58 | | | |

standardized normal variables) statistic. As can be seen in Tables 2 and 3, LC in the Refrigerator 2 and the Refrigerator 3 models is less significant revealing that other variables may have a stronger influence when the refrigerator is more energy efficient.

Refrigerator 2 had the second highest probability of adoption as predicted by the Probit model and this result appears to have been driven significantly by the rebate amount and the levelized cost variable. As compared to the Probit results for Refrigerator 3 (Table 3), the levelized cost variable still has a strong influence on the adoption of the second most efficient refrigerator.

The most energy efficient model, Refrigerator 3, appears to have been driven primarily by dwelling type (single family or multi-family), rebate amount, and climate zone (zones established by Edison reflecting weather patterns). These results reveal that the consumers may have been induced by higher rebate/cost ratios for the more efficient models. Also, the levelized cost variable has an increasingly diminishing impact as the efficiency of the refrigerator increases. This implies that other variables, such as the rebate amount, may supersede the levelized cost variable's explanatory power of the adoption of efficient refrigerators.

***Frequencies of Adoption of the Residential Measures.*** As mentioned above there were 112,392 observed implementations of DSM measures during the years 1990 through 1992. The frequency of the residential measures is illustrated in Tables 4 and 5.

The Probit model predicts similar shares to the actual shares exhibited in the population for residential measures. Frequencies in the population revealed, however, that Refrigerator 1 had a higher share than Refrigerator 2 which was contrary to the Probit results.

Table 4. Frequency of Adoption of Residential Measures

| Residential Measure | Frequency |
|---|---|
| Refrigerator 1 | 27,530/112,392 |
| Refrigerator 2 | 19,084/112,392 |
| Refrigerator 3 | 48,303/112,392 |

Single family residences adopted the largest number of efficient refrigerators in the population.

## Commercial/Industrial Space Conditioning Measures

There were fifteen Space Conditioning measures that were eligible for rebate under the Edison commercial retrofit and rebate program: (1) three types of air conditioners categorized by level of efficiency; (2) three types of heat pumps categorized by level of efficiency; (3) evaporative coolers; (4) window treatment; (5) roof/wall insulation; (6) air duct/pipe insulation; (7) chillers; (8) chilled water temperature controls; (9) clock thermostats; (10) time clocks; (11 ) electronic adjustable speed drives; (12) twist timers; (13) energy management systems; (14) economy cycling systems; (15) energy efficient motors; and (16) evaporative pre-coolers. Four of the measures did not have sufficient observations to estimate their loading order using the Probit technique: (1) window treatment; (2) air duct/pipe insulation; (3) chilled water temperature controls; and (4) high efficiency motors.

**Table 5.** Frequency of Adoption of Efficient Refrigerators by Dwelling Type

| Dwelling Type | Refrigerator 1 | Refrigerator 2 | Refrigerator 3 | Total |
|---|---|---|---|---|
| Single Family | 20,578 | 14195 | 31,439 | 66,212/ 112,392 |
| Multi-Family | 6,952 | 4,889 | 16,864 | 28,705/ 112,392 |
| Total | 27,530/ 112,392 | 19,084/ 112,392 | 48,303/ 112,392 | 94,917/ 112,392 |

***Interactive Measures.*** Table 6 lists the interactive measures and the rank ordering by the Probit technique and the levelized cost technique. Note, air conditioners, heat pumps, chillers, and evaporative coolers were not estimated as interactive pairs since they are mutually exclusive among themselves. As a result, there are four sets of interactive measures (Sets A-D) since each of the mutually exclusive measures (boldface) is interactive with the other measures in its set.

The ranking as determined by the Probit estimation was again based upon a combination of the P values and each model's AIC. Similar to the Commercial/Industrial Lighting measures, pairwise comparisons were made across measures within groups (Sets A-D) that were determined to be interactive. To eliminate additional multicollinearity, the pairwise comparisons were considered appropriate since there were many measures in the Space Conditioning end-use that were categorized as interactive. At times when comparing two measures the P Value and the AIC contradict, i.e. the P values favored one position in the order and the AIC favored another. In these cases, if the model fit was reasonable, i.e. a relatively low AIC, the P Value was chosen as the dominant criterion. Again, the P value represents the level of significance at which the independent variable can be said to make a contribution.

To exemplify the pairwise comparison, it was observed upon estimation that roof insulation was ordered behind the three types of air conditioners by consumers since the estimated probability of adopting roof insulation when used as an explanatory variable in the air conditioners' Probit models had a less significant impact, according to the P value, and the model fit was lower, as judged by the AIC. Roof insulation and the three types of air conditioners are interactive with other measures as well, yet, as stated above, to preclude overwhelming multicollinearity and preserve the integrity of the methodology, pairwise comparisons were made. Table 6 summarizes the established ordering based upon these runs.

To more completely illustrate the ordering of measures solely by levelized cost, Table 7 outlines the levelized costs by building type (Xenergy 1991) for measures where the information was available. Again, the least cost measures are in italics. One predominant conclusion that can be drawn from the table is that energy efficient air conditioners attain the lowest levelized cost for all building types except Retail. This observation concurs with the Probit results in the sense that air conditioners are also ranked above the other measures listed in Table 6.

***Frequenty of Adoption of Commercial/ Industrial Space Conditioning Measures.*** During the period from 1990 through 1992, there were 47,310 measures adopted under the commercial retrofit and rebate program. Tables 8-10 illustrate the breakdown for the most commonly adopted space conditioning measures.

Table 8 reveals that the Probit technique yields a reasonably accurate prediction of actual adoption based on

**Table 6.** Rank Ordering of Space Conditioning Measures

| Load Order | Set A | Set B | Set C | Set D |
|---|---|---|---|---|
| 1 | Clock Therms | Clock Therms | Clock Therms | Clock Therms |
| 2 | **ACs** | Time Clocks | Time Clocks | **Heat Pumps** |
| 3 | Time Clocks | Twist Timers | Twist Timers | Time Clocks |
| 4 | Twist Timers | Roof Insulation | Roof Insulation | Twist Timers |
| 5 | Roof Insulation | Economy Cycling Systems | Economy Cycling Systems | Roof Insulation |
| 6 | Economy Cycling Systems | Energy Mgt. Systems | Energy Mgt. Systems | Economy Cycling Systems |
| 7 | Energy Mgt. Systems | Electronic ASDs | Electronic ASDs | Energy Mgt. Systems |
| 8 | Electronic ASDs | **Evaporative Coolers** | **Chillers** | Electronic ASDs |

**Table 7.** Levelized Costs of Space Conditioning Measures (¢/kWh)

| Building Type | Air Conditioners | EMS | Chillers | Evaporative Coolers | ASD |
|---|---|---|---|---|---|
| Office | ***2.83*** | 3.00 | 3.10 | 5.65 | 6.95 |
| Restaurant | ***2.20*** | 2.30 | 2.40 | 4.95 | 5.40 |
| Retail | 4.39 | ***4.13*** | 4.28 | 8.10 | 9.67 |
| Food Store | ***24.00*** | 24.40 | 25.55 | 53.95 | 57.30 |
| Warehouse | ***17.80*** | 22.20 | 23.23 | 48.75 | 52.05 |
| Schools (K-12) | ***9.40*** | 10.40 | 10.85 | 22.40 | 24.03 |
| College/Trade Sch. | ***4.33*** | 4.50 | 4.70 | 9.70 | 10.50 |
| Health | ***2.12*** | 2.20 | 2.20 | 4.10 | 5.15 |
| Hotel | ***2.67*** | 2.80 | 2.90 | 6.05 | 6.60 |
| Misc. | ***3.93*** | 4.10 | 4.25 | 8.85 | 9.60 |

the actual population values. In this sense, the loading order as illustrated in Table 6 matches the frequencies of adoption in Table 8, i.e. those that were ordered first were also the most frequently adopted. Note that by far clock thermostats and air conditioners were the most popular space conditioning measures followed by heat pumps. Chillers and evaporative coolers were the least popular as revealed by both the Probit results and the population values. The population frequencies also reveal that twist timers, time clocks, roof insulation, economy cycling systems, and energy management systems were adopted at approximately the same rate.

**Table 8.** Frequency of Adoption of Space Conditioning Measures

| Measure | Frequency |
|---|---|
| Clock Thermostats | 5,209/47,310=.110 |
| Air Conditioners (Group 1) | 902/47,310=.019 |
| Air Conditioners (Group 2) | 1,008/47,310=.021 |
| Air Conditioners (Group 3) | 125/47,310=.003 |
| Heat Pumps (Group 1) | 390/47,310=.008 |
| Heat Pumps (Group 2) | 661/47,310=.014 |
| Heat Pumps (Group 3) | 29/47,310=.001 |
| Energy Management Systems | 494/47,310=.010 |
| Time Clocks | 465/47,310=.010 |
| Twist Timers | 444/47,310=.009 |
| Roof Insulation | 407/47,310=.009 |
| Economy Cycling Systems | 397/47,310=.008 |
| Adjustable Speed Drives | 236/47,310=.005 |
| Chillers | 100/47,310=.002 |
| Evaporative Coolers | 79/47,310=.002 |

**Table 9.** Frequency of Adoption of Space Conditioning Measures by Building Type

| Building Type | Evap. Cooler | Chiller | HP's | AC's |
|---|---|---|---|---|
| Office | 2 | 16 | 267 | 646 |
| Misc. | 13 | 14 | 73 | 289 |
| College/Trade School | 0 | 11 | 29 | 29 |
| K-12 | 0 | 2 | 232 | 282 |
| Health | 0 | 7 | 4 | 60 |
| Retail | 9 | 10 | 83 | 182 |
| Hotel | 6 | 12 | 110 | 37 |
| Food Store | 13 | 0 | 7 | 32 |
| Warehouse | 1 | 11 | 87 | 129 |
| Transportation | 0 | 0 | 7 | 1 |
| Manufacturing | 7 | 17 | 150 | 232 |
| Mining/Construction | 7 | 0 | 10 | 25 |
| Restaurant | 21 | 0 | 21 | 91 |
| Total | 79/47,310 | 100/47,310 | 1,080/47,310 | 2,035/47,310 |

**Table 10.** Frequency of Adoption of Space Conditioning Measures by Building Type

| Building Type | ASD | EMS |
|---|---|---|
| Office | 110 | 119 |
| Misc. | 8 | 15 |
| College/Trade School | 12 | 29 |
| K-12 | 6 | 88 |
| Health | 9 | 20 |
| Retail | 42 | 93 |
| Hotel | 4 | 16 |
| Food Store | 2 | 8 |
| Warehouse | 6 | 33 |
| Transportation | 0 | 4 |
| Manufacturing | 35 | 49 |
| Mining/Construction | 2 | 13 |
| Restaurant | 0 | 7 |
| Total | 236/47,310 | 494/47,310 |

Table 9 reveals that Offices and Schools (K-12) have a high adoption rate of air conditioners. Table 9 also reveals that heat pumps are most commonly adopted by Offices and Schools (K-12).

Most noticeably Table 10 reveals that Offices adopted almost half of the adjustable speed drives implemented for the period 1990-1992.

## Concluding Remarks

Three main conclusions can be drawn from this study. Primarily, when there are sufficient data, the Probit techniques used to estimate loading order of interactive measures are shown to be a reasonable complement to using levelized cost to rank measures. In the same vein, the Probit techniques prove to be a more complete manner in which to determine the technology shares of the mutually exclusive measures as opposed to using equal shares. The Probit algorithm has a high degree of out of sample predictive power as heuristically illustrated by the population frequency tables. Also, it is apparent that the probability of adoption and the loading order is building-type specific. Thus, a more disaggregated study using the Probit techniques may shed additional light on the subject. Finally, using more time series data would be helpful when measuring the change in consumer behavior over time. We encourage utilities to continue to add to their DSM databases in a similar manner as is the current practice such that future studies can capture a time element when determining the behavior surrounding DSM measure adoption.

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