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Aggregate Household Behavior in Heating and Cooling Control Strategy and Energy-Efficient Appliance Adoption

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***Abstract*—Using nationally representative household survey data administered by the U.S. Energy Information Administration, in this article, we attempt to analyze the aggregate behavior of households in terms of usage of appliances with explicit temperature control mechanism and the adoption of energy-efficient variants of other appliances. A multivariate probit analysis suggests that the households with larger size, higher income, and higher level of education are more likely to use smart thermostat to control temperature and purchase energy-efficient appliances. To identify the broad classes of household behavior, latent class analysis specifications are used. The optimal specification indicates that there are four broad classes of households. Consistent with the results of the multivariate probit specification, we find that the increased odds of belonging to the smart thermostat/energy-efficient appliance owner category of households over the no control/no energy-efficient appliance owner are related to variables, such as household type, size, and income. Therefore, targeting renters, apartment dwellers, and lower income households through appropriate household incentives and residential regulations are likely to improve outcomes in the adoption of efficient appliances and temperature control strategies.**

***Index Terms*—Demand-side management, energy efficiency, energy management, load management.**

I. Introduction

ENERGY efficiency has long been considered to be one of the most cost-effective ways to reduce greenhouse gas emissions [1], particularly in the residential sector that was responsible for around 20% of the total energy consumption in 2017 [2]. The residential sector has long been targets of policies and incentives to promote energy efficiency [3]. These include policies identifying appliances that would reduce long-term electricity consumption and reduce the payback period of purchasing these appliances through financial incentives [4]. These appliances are termed as energy-efficient appliances. Once a consumer purchases such an appliance, their energy usage behavior plays a significant role in determining the actual energy savings [5]. Electricity consumption, in general, is influenced by a myriad of other factors [6], such as the physical characteristics of the dwelling, including the type of building, house size, and house age; and demographic characteristics of the occupants including income, race, gender, age distribution, and level of education. The distinction between appliances that are "always ON" and those that operate in accordance with differing occupant behavior patterns is also important. There exists a fair bit of research on the linkage between the occupant behavior and energy efficiency. Kavousian *et al.* [6] note that households who tend to buy energy-efficient appliances are generally those with the higher levels of consumption and tend to be wealthier. Income is considered a potential factor for both higher level of consumption and the ability to buy higher priced energy-efficient appliances. A metastudy by Karlin *et al.* [7] demonstrates two strong behavioral dimensions—curtailment and efficiency, with curtailment measures being easier to adopt but less effective on a longer time horizon compared with the efficiency measures.

The theory of occupant behavior and its relationship to energy efficiency can be used as a backdrop to formulate the research questions for this article—*How can household behavior in terms of adoption of energy-efficient white goods*[1] *appliances and temperature control strategy of space heating and cooling equipment be jointly categorized (white goods refer to large electrical appliances)? What are the factors associated with the households being categorized into different behavioral groups?*

Following research parameters set up by Hong *et al.* [9], it is important to identify both the technical and social factors of occupant behavior. From the technical side, adoption and usage must both be considered for relevant appliances, given the asymmetric impact of appliances, such as heater and air conditioning, on total energy usage [10] with rebound effects being a larger concern for such appliances [11]. However, it is also to be noted that the way people use the temperature control for heating and cooling can differ significantly given that the effective use of thermostats is considered difficult [12]. A number of studies report that thermostats, in general, are improperly utilized [13], [14]. If the temperature setting of heating/cooling equipment and

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[1]White goods—A class of consumer durables that includes washing machines, dishwashers, refrigerators, tumble dryers, deep freezers, and cookers; they are so named because they are usually finished in white enamel paint … (Oxford Reference)

the adoption of other energy-efficient appliances are considered as the joint variables of interest, statistical analysis [15], [16] can enable us to determine the share of households that are using energy-efficient appliances but not using thermostats effectively versus those that are doing both.

From a social perspective, it is important to consider the factors that are closely associated with different behavioral patterns, e.g., demographics, household characteristics, or potential financial incentives [17]. Patterns demonstrated through the behavioral classification and characterization process can be used to improve the smart home demand response or demand management algorithms by providing data for better load segmentation and demand forecasting [18], [19]. The patterns can be used by policymakers to identify the characteristics of households that have significant shortcomings in the adoption of energy-efficient appliances and temperature control strategy. This information can be utilized to develop more effective targeting strategies on behavioral change [20], [21].

The rest of the article is structured as follows. Section II looks at the relevant existing literature that informs the research question and relevant gaps. Section III describes the data set and methods to answer the research question, followed by Section IV that gives results. Section V presents the discussion section that outlines how the key results of the article can be used as valuable inputs to several engineering and policy problems regarding residential energy efficiency, concluding the article.

II. Literature Review

Several studies look at the physical and social characteristics of households with regard to energy efficiency. A number of studies find that it is easier to undertake simple and short-term technical changes rather than long-term behavioral changes (e.g., buying an energy-efficient appliance versus optimally setting up a thermostat) [7], [8], [22]. More in-depth studies into social and other demographic factors [4], [23] find that statistically significant energy-efficient behavior is often associated with better economic and housing situation, higher education, relatively young age, and urban residency. Utility incentives are generally the strong predictors of energy-efficient behavior [24], [25]. Behavioral intervention programs have been employed with varying degrees of success, and meta analyses of the literature finds that benefits often tend to be short term [26]. That being said, regular feedback is good way to ensure that backsliding is minimized and long-term habits are formed [27]. The cost-effectiveness of such programs tends to vary with the literature estimates ranging between 1.1 cents/ kWh and 47.9 cents/kWh per a 2018 metastudy [28], although the authors find that the national average is around 2.8 cents/kWh in terms of net savings.

A potential application of understanding occupant behavior with regard to the efficient use of electrical appliances is the area of smart home demand management. This enables utilities and enrolled households to improve energy efficiency and lower the cost of energy consumption through two-way digital communications [29]. Smart home demand management relies on effectively characterizing and forecasting energy demand on the basis of dwelling and sociodemographic characteristics [6], [30]. The design of such a demand management system also requires understanding the usage pattern of different appliances, which can be used to design effective pricing strategies [31]. This can help schedule an application usage efficiently while minimizing user discomfort and cost [32] and maximizing demand response opportunities [19]. There are, however, also concerns that smart home technologies "may reinforce unsustainable energy consumption patterns in the residential sector" and lock out low income and vulnerable consumers [33]. In particular, it has been found that a number of households that do have smart appliances are not effectively able to use them, e.g., the improper use of programmable thermostats [13].

Thermostat usage data have been used by several studies to gauge the effectiveness of thermostat use. Temperature setpoint and setback strategies both have a significant impact on energy consumption [34], especially in colder or humid climate [35]. If the setpoint is only set slightly higher than what people generally do, a significant reduction in energy consumption can be achieved [36]. Smart thermostats can be effective in saving more energy compared with manual operation [37]–[39]; however, in the US context, it has been found that most people do not use the advanced features of their thermostats, which is somewhat related to their perceived complexity [12], [14].

The current literature regarding appliance energy efficiency, household behavior, and predictors has several gaps that this article seeks to address. While there has been literature dealing with the effect of having energy-efficient appliances or the usage pattern of appliances on consumption [40]–[42], there does not exist a lot of research that tackles the issue of identifying patterns of households, which do purchase energy-efficient appliances and engage in certain usage patterns jointly. There is a research regarding household types and adoption of energy-efficient appliances, but these do not provide a clear classification of households engaging in certain behavioral pattern compared with another. This article also extends on several studies that do try to look at multiple parameters of interest, such as knowing efficient appliances and purchasing them [45], or types, strategy, and financial value of energy-efficient measures adopted by households [22]. Households are classified through the statistical procedure of the latent class analysis [46]. The factors that affect the classification of a particular household into one category over another are then determined. Additionally, the article contributes to the growing literature analyzing the U.S. Energy Information Administration (EIA)'s Residential Energy Consumption Survey (RECS) database as well as the latent class analysis literature, which are discussed at greater detail in Section III.

III. Data and Methods

The EIA's RECS 2015 data set is utilized for this article. RECS is a household-level survey of a nationally representative sample of households that are asked questions regarding their energy-consumption-related behavior and relevant sociodemographic information. This is known as the housing characteristics part of the RECS data set [47]. The households are selected through a multistage sampling process. Of the 12 753 households sampled, only 5686 responded [48]. Note that the information on the primary sampling unit is not available in the public database. The RECS data set provides final sample weight, with the weight associated with each individual household adjusted for different probabilities of the selection and rates of response. The final weight associated with each household is the number of households in the population the particular sample household represents. There is a total of approximately 118.2 million households in the US represented by the RECS data set [48].

A. Data Set and Research Questions

The EIA RECS 2015 data set has several peculiarities in the response variables that influenced the research questions, in addition to the preexisting literature on the topic. Ideally, the classification process should have used adoption and usage data for all appliances considered, but since such data were not often available from the survey responses, several analytical choices were made.

Adoption data on energy-efficient space heating and cooling equipment are not available, unlike appliances such as washing machine, clothes dryer, refrigerator, and dishwasher. This means that the temperature setting strategy is not only useful as an indicator of occupant behavior but also as a proxy for the adoption of space heating and cooling equipment. This is a distinct change from the 2009 version of the survey, where the household adoption of these appliances was a survey question [49]. There are a number of indirect variables in the 2015 survey that may give us better understanding of the type of heating and cooling equipment owned, such as the presence of any thermostats, the presence of programmable thermostats, and the presence of smart thermostats. However, it is not clear whether they are applicable for heating or cooling systems apart from specific variables on the presence of thermostats and programmable thermostats for the central air conditioner.

Nonspace heating and cooling appliances do not have a lot of energy-efficient usage related questions associated with them in the 2015 survey. The closest to this is the variable "dishwasher cycle type used most of the time" in which "energy saver" is an option. However, unlike thermostats, the literature is relatively thin on the merits and demerits of various dishwasher cycles on energy efficiency compared with the actual work that gets done. One study [50] uses a specific dishwasher model to assess the demand-side management option, but the cycle choices are not easily replicable to a generic dishwasher model. A second study [51] looks at temperatures associated with cycle choices, in general, but does not explicitly quantifies the associated energy use. For this reason, the "dishwasher cycle type used most of the time" is not a variable chosen in this article.

Of the energy-efficient appliance adoptions that are considered—water heaters are excluded, specifically because there is no usage information associated with water heaters in the survey responses. Residential consumer end-use data from the same survey [52] show that water heating is almost important in terms of share in total energy consumption (14%) as space heating (15%) and air conditioning (17%). As a result, the authors are of the opinion that simply include the adoption of energy-efficient water heater, as a reasonable proxy for energy-efficient behavior was insufficient.

Specific utility incentives were not available from the data set, and the responses only pertained to generic incentives, such as "received utility or energy supplier rebate for new appliance or equipment" or "received tax credit for new appliance or equipment." This limited the analysis in terms of finding specific associations with the household classifications and the exact type of incentives received.

Finally, because the survey data are a snapshot of the sampled households at a given moment of time, the research question and the analysis could not consider the change in classification patterns or responses to incentives over time.

B. Variables

The following variables are utilized from the survey. Most of the variables were reconstructed in order to simplify the analytical process and to provide a more effective interpretation of the results. Summary statistics of the variables are presented in Table I.

1. Dependent Variables: Unless specified otherwise, the first option for each variable is the base category. In Table I, the order of possible values is listed as category 1–4 as applicable, following the order listed in this section.

1) Temperature setting strategy for cooling equipment (USEAC): The survey has separate questions regarding "central air conditioner household behavior" and "most-used individual air conditioning unit household behavior." If a household was indicated to have a central air conditioner, then responses to the first question were considered in constructing the variable. If a household was indicated to have window air conditioners (and not central air conditioners), then the responses to the second question were considered in constructing the variable. The strategy options are as follows:
   a) keep air conditioner (AC) temperature unchanged;
   b) manually change AC temperature (this includes turning the AC ON and OFF as needed);
   c) program the thermostat to automatically adjust the temperature during the day and night at certain times;
   d) no control over temperature (this is typical in the case of apartment buildings, where building management controls air temperature).
2) Temperature setting strategy for heating equipment (EQUIPMUSE): The survey has only one variable related to the temperature setting of heating equipment, "main heating equipment household behavior." The possible strategies are the same as the air conditioner case.
3) Adoption of noncooling/heating energy-efficient appliances (EFFICIENT): The responses regarding the adoption of several appliances are combined (energy-efficient versions as denoted by the presence of an energy star qualification)—namely refrigerators, clothes dryer, dishwashers, and clothes washers. This was done to reduce the number of dependent variables in the classification process, simplify the analytical process, and provide more meaningful interpretations. From a purely statistical point

TABLE I
SUMMARY STATISTICS FOR VARIABLES—CATEGORICAL VARIABLES AND NUMBER OF HOUSEHOLDS IN POSSIBLE CATEGORIES ($N = 5686$)

Variable	Category 1	Category 2	Category 3	Category 4
USEAC	2,030	2,127	781	748
EQUIPMUSE	2,156	2,176	972	382
EFFICIENT	1,753	3,519	414	-
TYPEHUQ	1,455	4,231	-	-
KOWNRENT	3,928	1,758	-	-
YEARMADERANGE	2,895	2,791	-	-
AUDIT	4,630	458	598	-
HHSEX	3,189	2,497	-	-
HOUSEHOLDER_RACE	3,189	2,497	-	-
EDUCATION	3,644	2,042	-	-
MONEYPY	3,147	2,539	-	-
INCENT	4,646	955	85	-
ELPAY	328	5,358	-	-
Variable	Mean	Median	Minimum	Maximum
NHSLDMEM	2.577383	2	1	12

of view, having more indicators can improve the quality of the classification process [53].

The possible options are the following.

1) Adoption of zero energy-efficient appliances, i.e., the household in question does not own an energy-efficient version of any of the four appliances.
2) Adoption of one or more energy-efficient appliances, i.e., the household in question owns an energy-efficient version for at least one of the four appliances.
3) Uncertain adoption of all applicable energy-efficient appliances, i.e., the household in question is uncertain regarding the adoption of an energy-efficient version for any of the four appliances.

2. Independent Variables: The number of categories was condensed from the original RECS survey responses for easier computation, specifically in the case of categories that had a numerical value attached to it, e.g., year of house construction and income. Unless specified otherwise, the first option for each variable is the base category. In Table I, the order of possible values is listed as category 1–3 as applicable, following the order listed in this section.

1) Type of house (TYPEHUQ): Not a single-family home (i.e., apartment or mobile home)/single-family home.
2) Adoption status (KOWNRENT): Nonrenter (i.e., owner or living without rent but not an owner)/renter.
3) Year of house construction (YEARMADERANGE): Before 1980/after 1980.
4) Energy audit status (AUDIT): No energy audit/energy audit taken place/uncertain audit status.
5) Respondent gender (HHSEX): female/male.
6) Respondent race (HOUSEHOLDER_RACE): Nonwhite (includes mixed race)/white.
7) Respondent education (EDUCATION): Below college education/college educated or above.
8) Household income (MONEYPY): Below $60000 per annum/$60000 per annum or higher.
9) Incent (INCENT): Received no utility incentives/received at least one utility incentive/uncertain regarding receipt of utility incentives.

The utility incentive responses considered are rebate for new appliance or equipment, free recycling of old appliance, tax credit for new appliance or equipment, and any other benefit or assistance.

1) Electricity payment responsibility (ELPAY): Household not fully responsible for separate payment of electricity/ household fully responsible for separate payment of electricity.
2) Number of household members (NHSLDMEM): Continuous variable—total number of household members. The summary statistics for this variable are specified in Table I.

Methods: A schematic workflow diagram that outlines the methodological structure of the analysis is presented in Chart 1. Table II presents the structure of the multivariate probit model that is outlined in Chart 1. Further details on each of the methods can be found in the Appendix.

IV. Results

A. Multivariate Probit Model

The first system had a reduced number of samples due to eliminating no-control households from USEAC1 and USHEAT1 variables; hence, only 68 draws were used.

For all systems, marginal effects are reported, as these are easier to interpret in the case of a probit model. The marginal effect with categorical independent variables can be interpreted as the change in odds of the household being part of the nonbase category for all three dependent variables, given a change to a certain category for the categorical independent variable from the base category. The results are summarized in Table III.

For System 1: Residents of single-family homes, a male respondent to the survey, college-educated respondent, a household with an income exceeding $60 000 per annum, and a household receiving one or more energy efficiency-related utility incentives were more likely to be using thermostats for heating and cooling as well as adopting one or more energy-efficient appliances, compared with using single/manual temperature control strategy and not having any energy-efficient appliances (or be uncertain). However, being a renter decreased these odds. The relationships are generally inline with what is seen in the literature, although with the respondent not necessarily being the head of the household, the gender and education link cannot be interpreted as strongly.

For System 2: Only income over $60000 seemed to increase the odds of the household belonging to the control temperature/having an efficient appliance category, which makes sense given the link between income and energy consumption and affordability of expensive appliances. There are a large number of variables that seem to decrease the odds of the household belonging to the control temperature/owning an efficient appliance category—being a renter, doing a home energy audit, the uncertain status of home energy audit, and the respondent being white. Being a renter makes sense from the empirical literature because rented houses often have their temperature controlled by management companies and there is limited opportunity to replace existing appliances or having uncertain audit status. There is little evidence to support the relationship between auditing and having no control over temperature/not buying an appliance and the respondent being white.

For System 3: Results are similar to that of System 1, which suggests that adding back the no-control group does not impact the relationships of the independent variables to thermostat usage/efficient appliance adoption very significantly.

An analysis of the three sets of correlation coefficients (in Table IV):

1) between heating and cooling temperature control strategy;
2) between heating temperature control strategy and energy efficiency (EE) appliance adoption;
3) cooling temperature control strategy and EE appliance adoption, suggests that predictably households will have fairly similar heating and cooling temperature control strategies.

However, there is a low (albeit statistically significant) correlation between their heating or cooling strategy with appliance adoption. This suggests that households may be as a whole purchasing one or more energy-efficient appliances but that does not necessarily inform their temperature control strategy.

B. Latent Class Analysis Model

The Akaike information criterion (AIC) and Bayesian information criterions (BICs) of 3–5 class models are presented in Table V. Only the class specification with the lowest AIC/BIC (bold values in Table V) is discussed in detail.

The 4-class model is the optimum one. The outcome of the model is summarized in Chart 2.

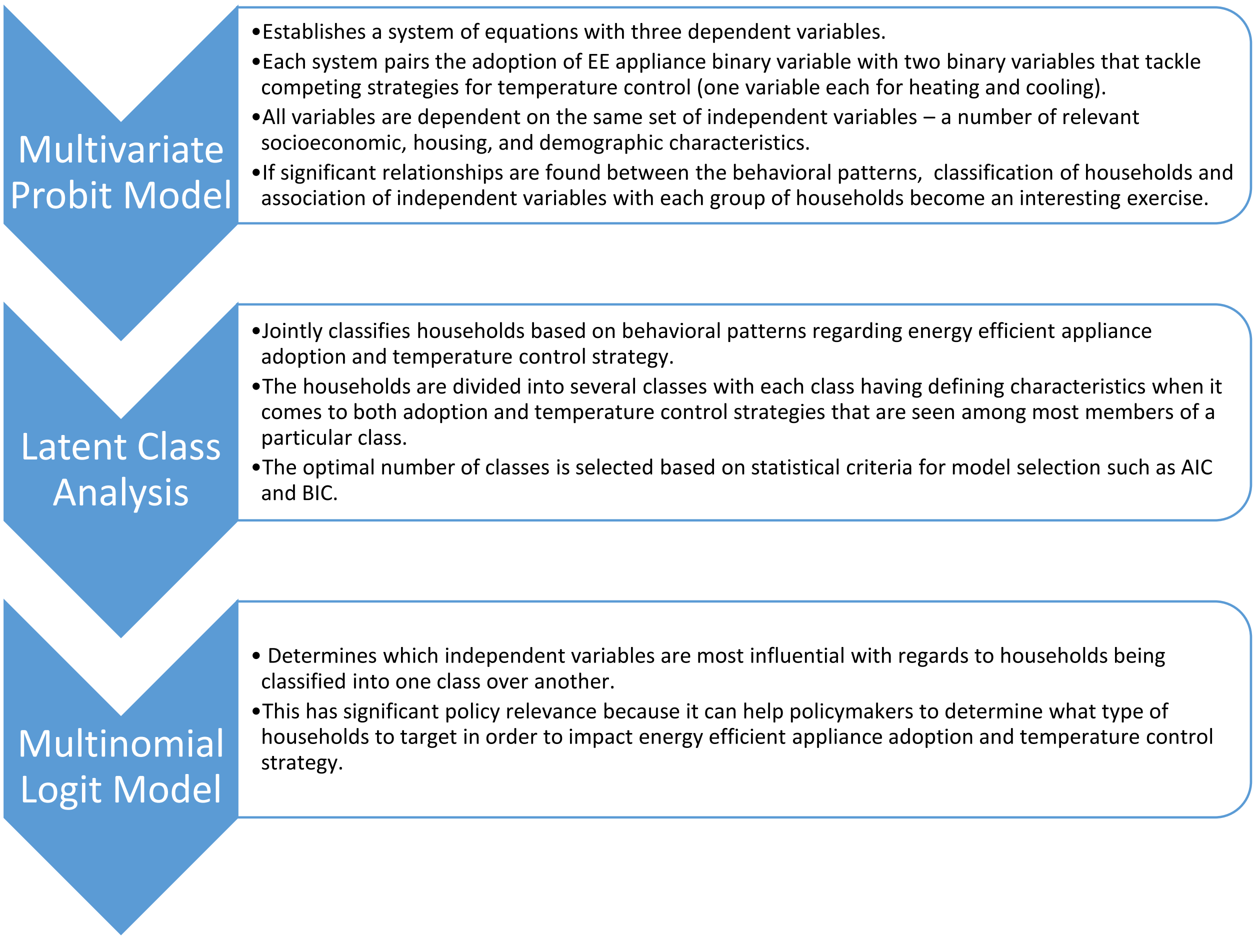
Effectively the four classes are largely separated based on the temperature control behavior. Apart from Class 4, most members of the other classes tend to own at least one energy-efficient appliance. The manual (Class 1) and single temperature (Class 3) strategy households dominate the sample in terms of percentage

TABLE II
REPRESENTATION OF THE MULTIVARIATE PROBIT MODEL

System	**Dependent Variables (Binary)**	**Independent Variables**
System 1	USEHEAT1 (Manual or Single Temperature in Heating vs Use of Programmable Thermostat) USECOOL1 (Manual or Single Temperature in Cooling vs Use of Programmable Thermostat) EFAPP (Adoption of zero/uncertain energy efficient appliances vs Adoption of one or more energy appliances)	These variables are common for all dependent variables across all three systems TYPEHUQ KOWNRENT AUDIT HHSEX HOUSEHOLDER_RACE EDUCATION INCENT ELPAY NHSLDMEM
System 2	USEHEAT2 (No Control of Temperature in vs Control of Temperature in Heating) USECOOL2 (No Control of Temperature in Cooling vs Control of Temperature) EFAPP (Adoption of zero/uncertain energy efficient appliances vs Adoption of one or more energy appliances)	
System 3	USEHEAT3 (No Thermostat Use in Heating vs Use of Programmable Thermostat) USECOOL3 (No Thermostat Use in in Cooling vs Use of Programmable Thermostat) EFAPP (Adoption of zero/uncertain energy efficient appliances vs Adoption of one or more energy appliances)	

of households being class members, which is inline with the literature. However, it is interesting to note that the programmable thermostat preferring class (Class 2) has a higher percentage of members owning one or more energy-efficient appliance compared with that of Class 1 and Class 3, suggesting some link between the high percentage of EE appliance adoption and exhibiting more-sophisticated temperature control behavior. The joint categorization into one class alone is not enough to draw the conclusive evidence. Class 4 is also interesting to analyze, and apart from the slight majority of its members not owning (or uncertain about owning) an energy-efficient appliance, it is the only class where heating and cooling temperature behavior splits. About half of the members do not have a control over the cooling strategy and there is an even split between the manual and single temperature strategy for heating. Much like Class 2, we can generally say that there seems to be a link between

CHART 1
Schematic Workflow Diagram Outlining Methodological Approach



less-sophisticated temperature control strategy and low adoption percentage of energy-efficient appliances.

C. *Multinomial Logit Model*

The model uses the 4-class prediction for each household as the dependent variable, with Class 1 (manual temperature strategy and EE appliance owning households) as the base class[2]. This means that the change in relative log odds of being in Class X (where $X \neq 1$) compared with Class 1 will increase/decrease by a certain value if moving from the base category of that independent variable to another category. In Table VI, only the independent variables that have a statistically significant relative log- odds of impacting a class change are reported (either positive or negative), along with the absolute numerical value of the odds in parentheses. A visual representation can be found in the Appendix.

[2]Class 1 is chosen as the base case because it is the most common category. We want to estimate what are the characteristics that are related to a deviation from the norm, especially the case where households use thermostats and the case where households do not own any EE appliance/have no control strategy. This is relevant from a policy perspective because potentially these households can be targeted to improve thermostat usage/ promote EE appliance ownership. The reason why Class 2 (owns EE appliance/ thermostat users) is not chosen as the base class is because we want to identify the characteristics that make the odds of not being in this class less likely (renters primarily) and potentially target these households for potential behavior change incentives.

The variables that are likely to increase the relative log odds of being a part of Class 2 (thermostat user/EE adoption) compared with Class 1 are residence in a single-family house, living in a house made after 1980, completion of a home energy audit, college-educated respondent, household income above \$60000 per annum, and use of at least one utility incentive. Renters and white respondents are likely to have decreased the relative log odds of being a part of Class 2. By and large the results are comparable to the first system of multivariate probit equations, where the base class was manual/single temperature strategy households and the alternate class was thermostat users. The only differences are the statistical significance of audit status in the multivariate probit analysis and the significance of being a white respondent in the multinomial logit analysis. However, the impact of race or gender of the respondent on behavior cannot be measured properly, if we do not know whether the respondent is the head of the household.

Between Class 1 and Class 3 (single temperature strategy/efficient appliance owners), there are very few variables that can affect membership relative log odds, which is to be expected given the similarities in the behavioral structure of the two classes. However, it does seem that the gender of the respondent (being male) and the education level (college educated) impact the relative log odds of membership, positively and negatively, respectively. While the relationship with gender

TABLE III
MARGINAL EFFECTS OF INDEPENDENT VARIABLES ON CHANGING ODDS OF THE HOUSEHOLD BEING PART OF THE NONBASE CATEGORY FOR ALL THREE-DEPENDENT VARIABLES, GIVEN THE CHANGE TO A CERTAIN CATEGORY FOR THE CATEGORICAL-INDEPENDENT VARIABLE FROM THE BASE CATEGORY

Independent Variable	System 1	System 2	System 3
	Marginal Effect (Standard Error)		
TYPEHUQ_SINGLEFAMILYHOME	0.238** (0.073)	0.019 (0.065)	0.301*** (0.075)
KOWNRENT_RENTER	-0.327*** (0.076)	-0.192** (0.064)	-0.303*** (0.068)
AUDIT_AUDITED	0.117 (0.095)	-0.232** (0.084)	0.079 (0.091)
AUDIT_UNCERTAIN	-0.016 (0.0.84)	-0.255** (0.074)	-0.016 (0.072)
HHSEX_MALE	0.127** (0.048)	0.034 (0.049)	0.119** (0.044)
HOUSEHOLDERACE_WHITE	-0.037 (0.066)	-0.249*** (0.060)	-0.069 (0.058)
EDUCATION_COLLEGE	0.276*** (0.052)	0.070 (0.056)	0.230*** (0.050)
MONEYPY_60K	0.305*** (0.053)	0.158** (0.057)	0.330*** (0.052)
INCENT_RECEIVED1+	0.158* (0.062)	-0.052 (0.067)	0.125* (0.059)
INCENT_UNCERTAINED	0.109 (0.162)	0.086 (0.209)	0.053 (0.173)
ELPAY_FULLYPAY	-0.106 (0.121)	-0.009 (0.098)	-0.194 (0.132)
NHSLDMEM	-0.014 (0.018)	-0.001 (0.019)	-0.008 (0.017)

Note: $*$ $p<0.05$; $**$ $p<0.01$; $***$ $p<0.001$.

is hard to interpret, having at least a college-educated household member may mean that there is some influence of not switching from a more-sophisticated strategy (actually changing the temperature, albeit manually) to a less-sophisticated one (keep a single temperature).

Changing relative log odds of membership between Class 1 and Class 4 (limited control/no EE appliance adoption) is positive as a result of being renters and uncertain audit status and negative due to living in a single-family home, living in a home constructed after 1980, having a college-educated respondent, and availing an utility incentive. The results make intuitive sense, given that renters and households with little knowledge about audits are likely to be correlated with those who have limited control over the setting temperature of their devices and not purchase any energy-efficient appliance. It is also likely that those living in a single-family home (typically not operated by management companies), newer house, having a college-educated respondent, and availing a utility incentive are less likely not to buy an energy-efficient appliance or not have control over temperature. This compares somewhat favorably with the second system of multivariate probit equations, where no control of heating and cooling temperature strategy was the base case

TABLE IV
CORRELATION COEFFICIENTS OF THE THREE-DEPENDENT VARIABLES UNDER THREE DIFFERENT TRIPROBIT SYSTEMS WITH STANDARD ERRORS IN PARENTHESES

System	**Correlation between Heating and Cooling temperature strategy (Standard errors)**	**Correlation between Cooling strategy and EE appliance adoption (Standard errors)**	**Correlation between Heating strategy and EE appliance adoption (Standard errors)**
System 1	0.92*** (0.01)	0.06*** (0.01)	0.06*** (0.02)
System 2	0.34*** (0.04)	0.08** (0.03)	0.01 (0.03)
System 3	0.89*** (0.01)	0.07*** (0.02)	0.07*** (0.02)

Note: * $p<0.05$; ** $p<0.01$; *** $p<0.001$.

TABLE V
AIC AND BIC COMPARISON FOR DIFFERENT LCA SPECIFICATIONS

Measure	**3-Class**	**4-Class**	**5-Class**
AIC	34032	**33912**	33915
BIC	34205	**34144**	34208

Endnote. AIC: Akaike information criterion; BIC: Bayesian information criterion. AIC and BIC are used to evaluate the relative quality of statistical models, with lower values indicating lower information loss in the specification concerned. Please see the Appendix for more details.

and having any type of control being the alternative case. There are two key differences. Variables that decrease the log odds in the multinomial logit case are not found to be significant in the multivariate probit system. Additionally, variables, such as audit status positive and white respondent, being not found significant in the multinomial logit analysis. These discrepancies can be explained by the fact that the multivariate probit system looked at all possible alternatives to no control as the counterfactual, while in the latent class analysis, the base class only comprises of manual temperature controlling households.

V. DISCUSSION

A. Engineering and Policy Implications

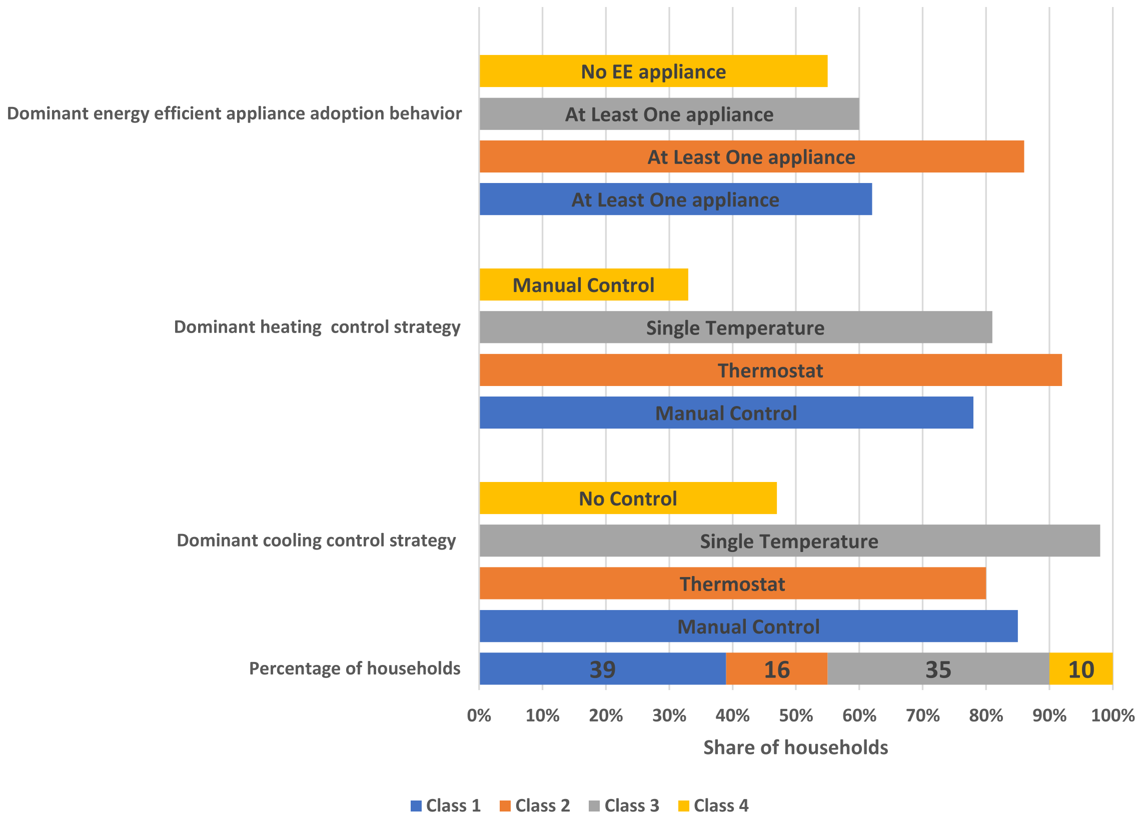
The joint analysis implies that while the majority of the sampled households' own energy-efficient appliances, only a small percentage controls temperature through thermostats, which is a residential setting that can lead to significant energy savings. Therefore, the adoption of one more energy-efficient appliance is not highly correlated with a consistent temperature control strategy. The 4-class categorization provides greater clarity in appliance usage even when adoption patterns are similar. In incentivizing households to adopt more energy efficiency measures, policymakers should ensure both adoption and proper usage of energy-efficient appliances. In determining whether households are using their appliances properly and helping households with regard to the ease of use, engineering solutions, such as smart meters and smart thermostats, are likely to be useful. These provide information on the thermostat usage patterns of individual consumers for the thermostat manufacturers.

The factors that are associated with the usage of programmable thermostats are home ownership, single-family home dwelling, higher income, college education, use of utility incentives, and completion of a home energy audit, and one factor explicitly reducing the odds of use of thermostats or increasing the odds of not controlling the temperature is renting. These factors are also generally inline with households that, in the literature, are generally classified as "proenvironmental" [17], [22]. Renters meanwhile have been studied in the literature as a subgroup of interest when it comes to energy efficient and stand out as a group when it comes to less effective energy efficiency outcomes [43], [63].

From the policy perspective, the literature that has analyzed the issue of energy efficiency adoption shortfalls [21] asserts

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

CHART 2
SUMMARY OF 4-CLASS SPECIFICATION OF HOUSEHOLD ENERGY-EFFICIENT BEHAVIOR



Note: All strategy and adoption numbers are in percentages. To be interpreted as the percentage of households within a particular class engaging in a particular type of behavior.

that policies should be tailored based on the failures that are noted in the system. For example, if there are market failures, such as imperfect information, policies to improve the quality of information to consumers should be developed and agents should be targeted as far as possible to improve the efficiency of investments. Based on our results, we make the following observations. First, a small percentage of the population uses the programmable features of thermostats. Whether they do so properly or not was beyond the scope of analysis for the survey and that is an important policy question. Second, this segment of the population tends to be educated and wealthy homeowners living in single-family homes—factors that themselves are highly interconnected (e.g., education and wealth, wealth to home ownership, and preference of single family home (SFH) in the case of home ownership). On the assumption that more people should use the programmable features of thermostats in order to improve the energy efficiency, policies should be designed to target those households that do not have factors that are associated with thermostat users, i.e., households that are low income, apartment dwelling (or mobile home dwelling), renters with less than college level of education, and those who typically do not avail any utility incentives or complete home energy audit. High-level information, such as energy star labels, do improve consumer awareness [45] but that does not necessarily help consumers who are low income or have other demographic issues that contribute to low regional ratings by organizations, such as the American Council for an energy-efficient economy [64]. Hence, states, utilities, and local authorities should consider the additional level of policy support for consumers in their jurisdiction exhibiting these demographic characteristics. Examples include nudge-style interventions, such as home energy reports, which have positively demonstrated effect on welfare [65], improvement of information provision that is relevant to the demographics under consideration [26], and setting incentive-compatible contracts, as well as financing options. Identifying the demographic characteristics of households that are not effectively exhibiting ideal energy efficiency behavior is also the first step toward designing intervention trials to evaluate new policies. It can also be used to design more-sophisticated consumption disaggregation techniques, such as nonintrusive load monitoring to improve stakeholder decision making [66].

From an engineering perspective, the insights may improve in managing and forecasting demand for smart home energy management. Some appliances, such as dryers, air conditioners, and dishwashers, may offer significant opportunities when it comes to demand response, so ascertaining the adoption and usage patterns of these appliances among households can be useful [19]. When it comes to create complex optimization algorithms for home energy management systems, well being of consumers can be better modeled by understanding broad usage patterns and demographical trends of the target households [18]. Analysis of smart meter data through clustering techniques has shown that demographic patterns are powerful predictors of daily usage patterns of electricity, which in turn can be used

TABLE VI
MULTINOMIAL LOGIT ANALYSIS OF INDEPENDENT VARIABLES AFFECTING THE RELATIVE LOG ODDS OF MEMBERSHIP OF A BEHAVIORAL CLASS COMPARED WITH THE BASE BEHAVIORAL CLASS (CLASS 1)

Membership change to	**Increased relative log-odds due to (odds specified in parentheses)**	**Decreased relative log-odds due to (odds specified in parentheses)**
Class 2	TYPEHUQ_SFH (0.696)***	KOWRENT_RENTER (0.796)***
	YEARMADE_1980+ (0.173)*	HOUSEHOLDERACE_WHITE (0.265)*
	AUDIT_AUDITED (0.309)*	-
	EDUCATION_COLLEGE (0.373)**	-
	MONEYPY_60K (0.538)***	-
	INCENT_AVAILED (0.309)*	-
Class 3	HHSEX (0.130)*	EDUCATION (0.481)***
Class 4	KOWRENT_RENTER (0.404)**	TYPEHUQ_SFH (0.409)***
	AUDIT_UNCERTAIN (0.384))*	YEARMADE_1980+ (0.684)***
	-	EDUCATION (0.325)*
	-	INCENT_AVAILED (0.476)*

Notes: Class 1: EE appliance owning manual temperature control class; Class 2: EE appliance owning thermostat temperature control class; Class 3: EE appliance owning single temperature class; Class 4: Non-EE appliance owning mostly no control/manual temperature control class.

to generate effective load profiles [67]. While not as extensive as daily or hourly data gathered from smart meters, the RECS data set is extensive enough for predicting further patterns in the context of electricity usage and household behavior by using machine learning techniques, such as clustering, and can be used to make further contribution to the existing literature [68], [69].

APPENDIX

Further methodological details.

A. *Multivariate Probit Model*

This article uses the “triprobit” add-on of Stata [57] to undertake the analysis. A total of 75 draws ($\sqrt{5686} = 75.4$) are used in this article due to the recommendation of the number of draws being roughly the square root of the sample size [58]. The add-on also allows the use of probability weighting, and the final sample weights from the database are used for this purpose.

Triprobit estimates simulated maximum-likelihood three-equation probit models using the Geweke–Hajivassiliou–Keane smooth recursive simulator. The mathematical process is summarized in the notes of the author of the triprobit add-on [59]

$$\begin{aligned} y_1 &= 1 \text{ if } X\beta + \varepsilon_1 > 0 \\ &= 0 \text{ otherwise} \end{aligned} \tag{1}$$

$$\begin{aligned} y_2 &= 1 \text{ if } Z\gamma + \varepsilon_2 > 0 \\ &= 0 \text{ otherwise} \end{aligned} \tag{2}$$

$$\begin{aligned} y_3 &= 1 \text{ if } W\theta + \varepsilon_3 > 0 \\ &= 0 \text{ otherwise} \end{aligned} \tag{3}$$

with

$$\begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \end{bmatrix} - > N(0, \Sigma). \tag{4}$$

X, *Z*, and *W* are the respective vectors of independent variables associated with these binary variables; β, γ, and θ are the corresponding coefficients; and ε_1, ε_2, and ε_3 are the error terms. Essentially, $X\beta + \varepsilon_1$, $Z\gamma + \varepsilon_2$, and $W\theta + \varepsilon_3$ can be considered as the specifications of continuous latent variables associated with y_1, y_2, and y_3 (assume $y_1^* = X\beta + \varepsilon_1$, $y_2^* = Z\gamma + \varepsilon_2$, and $y_3^* = W\theta + \varepsilon_3$). We assume that the binary variables take on the value one only if the value of the underlying latent variables are positive.

B. Latent Class Analysis

Latent class analysis (LCA) can be undertaken using sample weights within Stata [60]; however, this led to the convergence issues when using the data set in the article. As a result, sample weights are not used; hence, the interpretation of the LCA results cannot be easily generalized to the entire population. For computational efficiency, the R package "poLCA" was used for latent class analysis [61]. A short description of the process, following the poLCA documentation, is provided in the following.

Assume there are J polytomous categorical variables, each with K_j possible outcomes, with each variable likely to have different numbers of possible outcomes indexed by j. Let the individuals to which these outcomes are attributable to be indexed by $i = 1,\ldots,N$. Denote

$$\begin{aligned} Y_{ijk} &= 1 \quad \text{if the } i\text{th individual gives the} \\ &\qquad k\text{th response to the } j\text{th variable} \\ &= 0 \quad \text{otherwise.} \end{aligned} \tag{5}$$

The model approximates the observed joint distributions of the categorical variables as a weighted sum of a finite number R. This R is predetermined and is known as the number of latent classes. Assume, π_{jrk} being the class-conditional probability that an observation in class $r = 1,\ldots,R$ produces the kth outcome for the jth variable. Furthermore, define p_r as the prior probabilities of the latent class membership.

We can define probability that an individual i of class r produces as a particular set of J outcomes as follows:

$$f(y_i, \pi_r) = \prod_{j=1}^{j} \prod_{k=1}^{K_j} (\pi_{jrk})^{Y_{ijk}}. \tag{6}$$

The probability density function can be defined as follows:

$$P(Y_i | \pi, p) = \sum_{r=1}^{R} \prod_{J=1}^{j} \prod_{k=1}^{K_j} (\pi_{jrk})^{Y_{ijk}}. \tag{7}$$

Given estimates of p_r and π_{jrk}, that can be estimated from the model, we can determine the posterior probability that each individual belongs to each class, conditional on the observed values of the categorical variables, can be calculated as follows:

$$\hat{P}(r_i | Y_i) = \frac{\hat{p}_r f(Y_i; \hat{\pi}_r)}{\sum_{q=1}^{R} \hat{p}_q f(Y_i; \hat{\pi}_q)}. \tag{8}$$

The latent class model parameters are estimated by maximizing the following log-likelihood function.

$$\text{InL} = \sum_{i=1}^{N} \text{In} \sum_{r=1}^{R} p_r \prod_{j=1}^{J} \prod_{k=1}^{k_j} (\pi_{jrk})^{Y_{ijk}}. \tag{9}$$

A total of 3–5 class models are evaluated and the optimal class number is chosen on the basis of goodness of fit criteria focusing on parsimony. The poLCA package calculates AIC and BIC automatically. Preferred models are those that minimize the values of the BIC and/or AIC. Low AICs and BICs are represented by higher values of log likelihood, lower number of estimated parameters, and smaller number of total observations. Since across classes, the number of observations is the same, most efficient fit in terms of the number of classes is obtained by higher log-likelihood values and lower number of estimated parameters.

The posterior probabilities of each household being assigned to a certain class are assigned to provide a class assignment to each household, which is then used in the following step.

C. Multinomial Logit Model

Stata's mlogit command is used for the analysis of the multinomial logit regression. A summary of the theoretical description of the model is described by Greene [62].

Consider Y being a vector of categories for the dependent variable, with values ranging from Y_1 to Y_J, indexed as Y_i denoting the choice for the ith individual in the data set. If X denotes the set of explanatory variables, with x_i being the vector of the explanatory variable for the ith individual.

The probability of ith individual picking the jth choice is denoted by

$$\text{Prob}(Y_i = j) = \frac{e^{\beta'_j x_i}}{\sum_{k=0}^{j} e^{\beta'_k x_i}}. \tag{10}$$

The model as it stands in (1) is undetermined. A convenient normalization that solves the problem is $\beta_0 = 0$. This leads to

$$\text{Prob}(Y_i = j | x_i) = \frac{e^{\beta'_j x_i}}{1 + \sum_{k=1}^{J} e^{\beta'_k x_i}}. \tag{11}$$

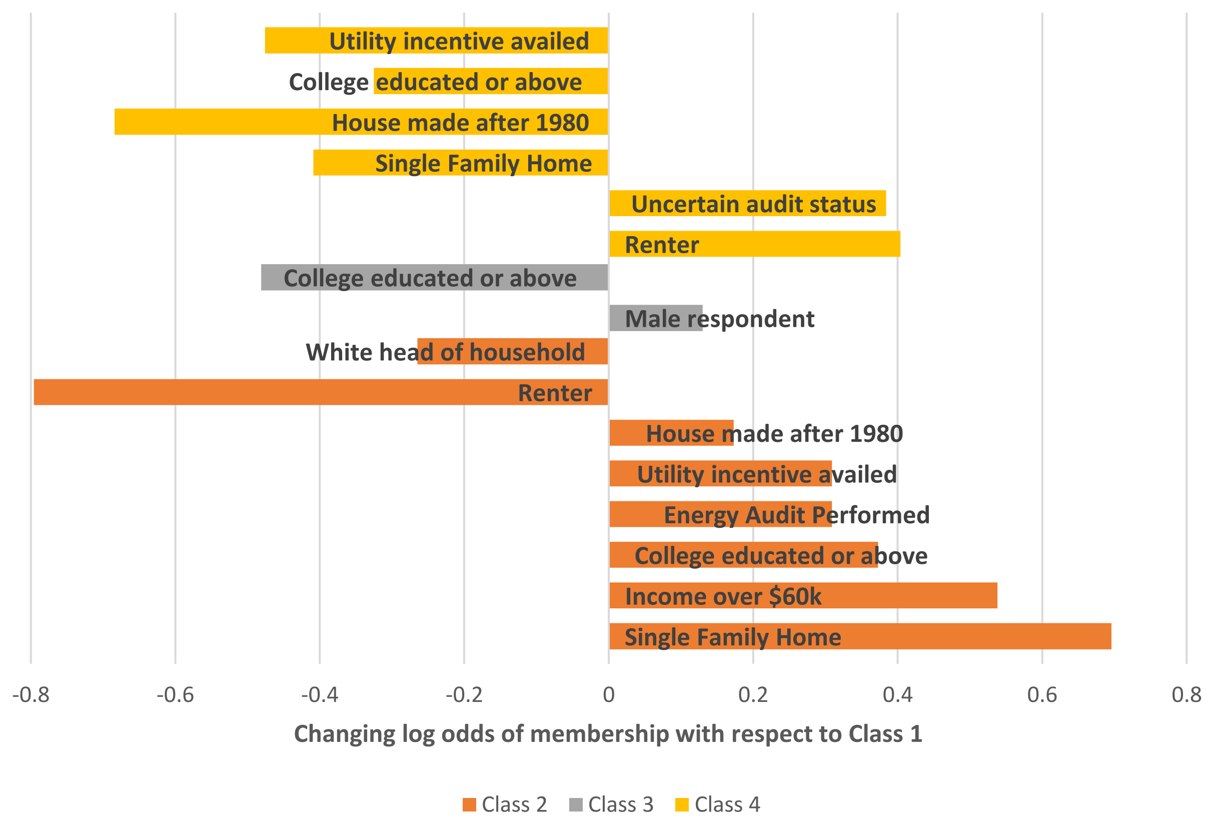
From (2), if $k = 0$, we can calculate log odds ratios given by

$$\text{In}\left[\frac{p_{ij}}{p_{ik}}\right] = x_i\left(\beta'_j - \beta'_k\right) = x_i \beta'_j. \tag{12}$$

The denominator of the conditional probability equation remains unchanged, i.e., it is not affected by the choice of j. For notational convention, assume Prob $(Y_i = j | x_i)$ can be written as p_{ij}. Therefore, taking the log on both sides, assuming $Y_i = j$ gives us $\ln(p_{ij}) = \beta\prime_j x_i$. For a baseline Y$i$ = k, the choice against which the odds of j is calculated, $\ln(p_{ik}) = \beta\prime_k x_i$. Therefore $\ln(p_{ij}/p_{ik}) = x_i(\beta\prime_j - \beta\prime_k) = \mathrm{x}_i\, \beta\prime_j$ if $k = 0$.

D. Visual Representation of the Multinomial Logit Model Results

CHART 3
INDEPENDENT VARIABLES AFFECTING LOG ODDS OF MEMBERSHIP IN CLASS 2–4 COMPARED WITH CLASS 1



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