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Lifestyle factors in U.S. residential electricity consumption

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ABSTRACT

A multivariate statistical approach to lifestyle analysis of residential electricity consumption is described and illustrated. Factor analysis of selected variables from the 2005 U.S. Residential Energy Consumption Survey (RECS) identified five lifestyle factors reflecting social and behavioral patterns associated with air conditioning, laundry usage, personal computer usage, climate zone of residence, and TV use. These factors were also estimated for 2001 RECS data. Multiple regression analysis using the lifestyle factors yields solutions accounting for approximately 40% of the variance in electricity consumption for both years.

By adding the household and market characteristics of income, local electricity price and access to natural gas, variance accounted for is increased to approximately 54%. Income contributed ~1% unique variance to the models, indicating that lifestyle factors reflecting social and behavioral patterns better account for consumption differences than income. Geographic segmentation of factor scores shows distinct clusters of consumption and lifestyle factors, particularly in suburban locations. The implications for tailored policy and planning interventions are discussed in relation to lifestyle issues.

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1. Introduction

The concept of "lifestyle" has been periodically addressed in relation to the social and behavioral aspects of energy consumption. *Lifestyle* is defined by Lutzenhiser and Gossard (2000) as "distinctive modes of existence that are accomplished by persons and groups through socially sanctioned and culturally intelligible patterns of action." This definition implies specific clusters of social, demographic and behavioral patterns that influence expenditures, consumption, and ultimately, use of energy. The lifestyle concept has long been used in consumer research and advertising, as recognized lifestyle subgroups constitute distinct markets. The relevance of lifestyle to energy consumption is illustrated by findings that similarly structured households with identical physical shells are associated with widely varying energy usage (Socolow, 1977/78; Schipper et al., 1989; Lutzenhiser and Gossard, 2000). More detailed analysis of variables such as income and energy price shows relatively weak, and sometimes ambiguous or paradoxical relationships with consumption (Lutzenhiser, 1993; Herter and Wayland, 2010; Karanfil, 2009; O'Neill and Chen, 2002). We have reported elsewhere on preliminary investigations of lifestyle factors (Sanquist et al., 2010), and expand upon that work in this paper.

While the term "lifestyle" can be emotionally laden and sometimes associated with curtailment or deprivation in discussions of energy efficiency and conservation (Nader and Beckerman, 1978), our own and other research has shown it to be a useful concept for identifying specific energy reduction opportunities, based on quantitative analysis (Sanquist et al., 2010). Lifestyle may be broadly conceptualized as patterns of consumption influenced by decisions at various points across the lifespan, such as what profession to engage in, where to live, when (or whether) to marry and have children, and more proximal choices regarding what to purchase and how and when to operate energy consuming equipment. This conceptualization suggests that analysis of lifestyle and energy consumption needs to encompass not only the traditional demographic segmentation elements, but also information about what people own and how they use it.

This report is concerned with developing a quantitative, multivariate model of lifestyle factors in relation to U.S. residential electricity consumption. We focus on electricity consumption specifically for several reasons: (1) the proliferation of consumer electronics represents a growing source of electricity consumption that is likely reflected in social, cultural, demographic and behavioral measures (International Energy Agency, 2009); (2) the increasing interest in "behavioral wedges" to reduce energy usage through efficiency and conservation has clear implications for a

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range of residential electricity end uses (Dietz et al., 2009), and (3) the rapid development of "smart grid" technologies for changing consumption patterns through feedback can benefit from better knowledge of the lifestyle factors that influence energy consumption (Ehrhardt-Martinez et al., 2010).

2. Background

Lifestyle research in relation to energy consumption began to appear in the 1970s to describe broad clusters of activity, such as location of residence, type of car driven, etc. Anthropological and sociological analyses of lifestyle and energy consumption have been provided by Nader and Beckerman (1978), Lutzenhiser and Gossard (2000) and Wilhite et al. (1996). The common theme among these treatments is the linkage of value preferences to consuming behavior. Sobel (1981), for example, argues that the current "consumer culture" represents a means of social control through wages and the ability to express individual preferences by product choices. The specific nature and extent of consumption is considered a reflection of lifestyle preferences. Recent analyses of changing consumption patterns in China, for example, add credence to this general explanation (Shui et al., 2010). While increased energy consumption is associated with increased quality of life, analysis of various social indicators suggest that there is considerable latitude for energy reduction without adversely affecting social well-being (Mazur and Rosa, 1974).

Lifestyle analysis in the marketing domain developed through the combination of demographic, social, and psychological measures (Plummer, 1974). The focus on lifestyle traits or psychographics, as distinct from more abstract personality variable and attitudes, is meant to describe consumer behavior more directly (Lastovicka, 1982). Factor analysis and other statistical clustering methods are used to define relatively homogeneous *segments* that are useful for understanding purchasing behavior. The basic theory of this type of work is that lifestyle measures reflect latent traits that are expressed in consumption. By understanding these patterns, advertising campaigns and other means of influence can be developed to shape consumer behavior.

This type of analysis has been applied at a basic level by Van Raaj and Verhallen (1983) to describe patterns of residential energy behavior (e.g., conservers, spenders, cool, warm). The study design involved factor analysis of reported energy usage behaviors, and clustering was conducted on the basis of principal component scores. While the results tend to be quite specific to temperature control, the study demonstrates that analysis of behavioral usage is important to understanding patterns in energy consumption that may not be evident in social or demographic clustering. Related results were reported by Cramer et al. (1984)—self-reported frequency of usage for air conditioning accounted for as much variance in electricity consumption as structural features of the house. In a comprehensive analysis of energy use and how people spend their time, Schipper et al. (1989) concluded that increases in quality of life (i.e., ownership of equipment and infrastructure) will not be the primary driver of energy demand; instead it will be the type, frequency, and duration of various personal activities. They recommend a behavioral and time-based approach to complement technical energy analysis. While Schipper et al. (1989) did not anticipate the proliferation of personal electronics and miscellaneous electrical loads, the focus on the personal activity basis of energy usage is adaptable to the variety of plug loads now in use.

Energy analysis by government agencies such as the Energy Information Administration (EIA) has typically employed a *sectoral* approach involving residential, industrial, commercial, and transportation segments. Re-analysis of sectoral data by Shui and Dowlatabadi (2005) suggests that individual consumers, represented by the residential component, account for the largest share of energy consumption in the U.S. This is because the *direct* consumption of energy by individual consumers is supported by *indirect* energy usage in the other sectors, as well as in the production of energy. This suggests that more detailed analysis of residential consumption can identify specific *lifestyle factors* associated with energy use, based on multivariate analysis of consumer behavior. Further, by assessing the usage data from prior-year surveys, the stability and generality of lifestyle energy consumption factors can be assessed.

There has been an increase in the amount of data available for this type of analysis in recent Residential Energy Consumption Surveys conducted by the U.S. Department of Energy, including more detailed questions concerning miscellaneous electrical loads and usage. These data can support an enriched approach to analysis of residential energy consumption, to complement prior analyses that have been based primarily on household demographic variables. Specific lifestyle dimensions can be defined with factor analysis to develop composite variables expressing relationships between demographics, technology choices, usage, and preferences. Further use of those lifestyle factors as predictors in multiple regression can indicate their relative importance in predicting energy usage, and thus identify prospective targets for efficiency and conservation interventions, such as smart grid-based in-home display technologies. Based on the findings reviewed above, we expect that lifestyle factors will be dominant predictors of electricity consumption, with variables such as income and price having a relatively small influence.

3. Method

3.1. Data

The Residential Energy Consumption Survey (RECS) is a national household energy survey conducted by the Energy Information Administration (EIA) of U.S. Department of Energy every three years. There have been 12 surveys since it was first conducted in 1978. This study is based on the 2005 survey, the most recent one at the time of this study.

The 2005 RECS collected data from 4382 households in housing units statistically selected to represent 111.1 million housing units in the U.S. that year (U.S. Energy Information Administration, 2005). In this study, we focused on 2165 single houses that have their annual electricity bill collected from utility companies. The 2001 RECS collected data from 4822 households; from this sample we used 2690 single households that provided utility bill data. The RECS variables cover the physical characteristics of the housing units, household demographic characteristics, appliances information such as age, size, and usage, fuel types and related consumption.

A subset of the RECS variables reflecting lifestyle patterns was selected for factor analysis. These variables represent geographic location, household equipment/appliances and usage, and family structure. Additional variables were used separately in regression—these reflect specific household characteristics including local electricity price, income, and access to natural gas. Some variables drawn from the 2005 and 2001 data set were transformed based upon statistical and modeling considerations. For example, price, income, and energy use variables were Ln-transformed in preparation for later analyses.[1] Multilevel categorical variables (e.g., type of air conditioning) related to differing levels

[1] Ln-transformation serves to (a) linearize anticipated multiplicative relationships between these variables, and (b) disassociate the proportional relationships between means and standard-deviations seen when dividing the sample population into various segments (see Scheffe' (1959) for discussion).

Table 1
RECS variables used for factor analysis and nominal relationship to lifestyle patterns and concepts.

Lifestyle element	Variable	Description	Mean	SD
Where to live	**Cooling degree days**	Number of degrees per day that the dailyaverage temperature is above 65 Fahrenheit	1365.6	861.2
	Heating degree days	Number of degrees per day that the dailyaverage temperature is below 65 Fahrenheit	4532.3	2109.9
	Age of house	Age of house	38.4	24.4
Appliances owned, frequency of usage	**Oven use, electric**	Times per week oven is used	2.4	2.4
	Dish washer use	Dish washer loads per week	2.5	3.2
	Clothes washer use	Number of washer loads per week	5.7	3.8
	Clothes dryer Use, electric	Number of dryer loads per week	3.7	4.0
Thermal comfort	**Number ceiling fans**	Number of ceiling fans used in house	2.9	2.1
	Scaled air conditioning[a]	Type of air conditioning the house uses	1.05	0.03
	Natural log of total cooled square feet	Natural log of square feet air conditioned house	5.8	3.0
Information technology, entertainment ownership and usage	**Number TVs**	Number of TVs in the house	2.8	1.3
	TV use	Hours per week TV is on	33.8	20.1
	Number PCs	Number of computers in household	1.2	1.1
	PC time on total, weekly	Computer hours on per Week	44.0	82.6
Family composition and routines	**Hours per day light bulbs are on**	Total hours lights are on per day	19.6	22.8
	Number household members	Number people living in the house	2.8	1.5
Electricity consumption	**LNKWH**	Natural log of KWH use (from bill)	9.2	0.6

[a] Scaled air conditioning is a variable constructed on the basis of several categorical variables reflecting the type of AC used in the home—none, room, central and central+room. These categorical variables were run in a regression against LKWH, and the resulting regression coefficients used as a basis for a scaled variable.

of energy use were scaled into single continuous variables. The transformations were performed to avoid the forming of quasi-factors, based simply on the variable structure. The final set of RECS variables used for the lifestyle factor structure analyses is contained in Table 1.

For the analysis presented in this paper, we consider *lifestyle variables* to be mediators of electricity consumption. We also address the specific *household characteristics* of income, electricity price, and access to natural gas. We treat these variables individually as they are conceptually distinct, and by analyzing them separately we can assess the degree to which these variables contribute independently unique variance to electricity consumption.

3.2. Modeling approach

While existing econometric approaches focus on quantitative variables such as household income and weather (Silk and Joutz, 1997; Narayana et al., 2007; Dergiades and Tsoulfidis, 2008), and engineering modeling is based on the technical characteristics and fuel use of key appliances (Swan and Ugursal, 2009; Kavgic et al., 2010), this study explores the role of lifestyle dimensions by employing factor analysis and multiple regression analysis. This represents a statistical approach to bottom-up energy modeling, with a focus on consumer social and behavioral factors. Factor analysis was employed to reduce the number of variables, identify underlying constructs that express correlated independent variables, and to detect structure and relationships between them. By applying the factor structure and regression weight derived from 2005 data for analysis of 2001 data, the stability and generality of the factor model over time can be assessed.

Factor analysis was conducted using a three-step process that first included and then excluded electricity use. Initially including electricity use ensured that single lifestyle variables related to it, but not other such variables, would be identified as defining a single-variable lifestyle dimension. Initial inclusion also bolstered the odds of capturing weaker variable components and thereby served to ensure that the resulting solution would be comprehensive. Electricity use was ultimately excluded from the process of factor identification and scale score estimations. This sets the stage for an evaluation of the utility of resultant lifestyle factors for predicting both 2005 and retrospective energy use from the 2001 RECS data set. Preliminary exploratory analysis using principal components analysis suggested that a 5-factor solution was appropriate, based on the scree plot and the number of factors with eigenvalues greater than one.

During this second stage, a five-factor unweighted least squares (ULS) analysis was conducted on the correlations of the 17 variables adapted from RECS-2005 using SPSS/*PASW*-18 (cf. Norusis, 2011).[2] Jöreskog (2003) has advocated this technique as particularly "robust" in that it does not require specific assumptions about the distribution of the data. The ULS five-factor solution altogether accounted for 45.5% of the total variation in the 17 lifestyle-related variables and 45.3% of the total in the 16 less LNKWH. The ULS was followed by an orthogonal (varimax) rotation that provides for simple structure (Harman, 1976; Norusis, 2011).

Initial factor-scale scores for the sample of RECS-2005 individual users ($N=2165$) were automatically computed via the "regression method" for five lifestyle-factors (discussed further in the Results section). Subsequently, regression analyses were conducted using all but LNKWH as the 16 independent variables and the set of *initial factor-scale scores as the respective dependent variables*. These resulted in (1) five lifestyle factor-scale score estimation equations that are based only on the first 16 lifestyle variables (i.e., without LNKWH) and (2) five sets of lifestyle factor-scale scores for each of the households analyzed in RECS-2005. The first of these was used to compute the second, but may be applied in principle to any future RECS sample where the 16-lifestyle variables are measured. The second of these, the respective lifestyle factor-scale scores, was employed in later explorations of their relationship with LNKWH using multiple regression.

Two regression analyses were conducted to evaluate relationships between five lifestyle factor-scale scores and 2005 energy

[2] ULS has a long history and several "seemingly divergent" computational approaches that yield essentially identical results (SPSS, 1997; Jöreskog, 2003; Norusis, 2011). The algorithmic variations are signaled by other names (e.g., MINRES and Iterated Principal Axis) that have sometimes confused analysts and led to its unfortunate avoidance. Joreskog has recently shown the mathematical equivalence of most of the computational variations.

use (LNKWH). The first of these included only the five lifestyle factor-scores—derived above—as predictors. The second analysis included three other household characteristics in order to explore their additive contributions, i.e., Natural Log (Ln) Income, Natural Gas Available (via Pipeline), and Natural Log (Ln) Price/KWH. The regression coefficients resulting from this final analysis provide an assessment of the unique contributions of both the lifestyle and additional variables.

Two regression analyses were conducted to evaluate the predictive stability of the lifestyle factor estimates when computed from the 2001 RECS data. To perform this analysis, lifestyle factor scores were estimated for 2001 using regression weights derived from the 2005 data. The 2001 lifestyle factor regression weights differed slightly from those employed earlier for computing 2005 factor scale scores, as one of the 2005 variables "TV Use" was not measured in 2001. In the 2005 data, this would have reduced the reliability of the TV Use lifestyle factor to 0.43 from 0.47, but not otherwise changed the reliabilities. The anticipated impact of this reliability reduction would be a slight reduction in the proportion of variance accounted for by the 2001 lifestyle factors (vs. 2005).

4. Results and discussion

4.1. Basic descriptive statistics

The average income for the sample of 2165 respondents is \$54,345 ($SD=35,330$), and the average annual electricity usage in KWH is 12, 237 ($SD=7416$). Of particular note is the standard deviation in electricity usage. Between the low and high ends of the range, usage varies by a factor of four. Fig. 1 illustrates the range of electricity usage across the geographic regions sampled by RECS.

The geographic pattern maintains the high level of variability illustrated by the overall sample summary, and also portrays the impact of various climate regions, such that the South Atlantic, East South Central and West South Central regions consume the largest amount of electricity. This is due to the much higher number of cooling degree days in these areas, and the increased use of air conditioning in these conditions.

Fig. 2 illustrates the relationship between income and electricity usage for the RECS sample. There is a modest correlation (0.26) between income and electricity usage, but the principal feature of this figure is again the *range* of usage around the mean. For virtually all income categories, the range of usage varies by a factor of three or four.

4.2. Factor analysis results

Table 2 provides the results of the factor analysis solution that appears to best represent the lifestyle elements reflected in the independent variables measured by RECS. Table 2 shows the resulting factor structure, with interpretive labels, and the loadings (correlations) of the input variables with these factors.

Examination of the table reveals that each of the resulting five factors are essentially defined by just two prominent (>0.40)

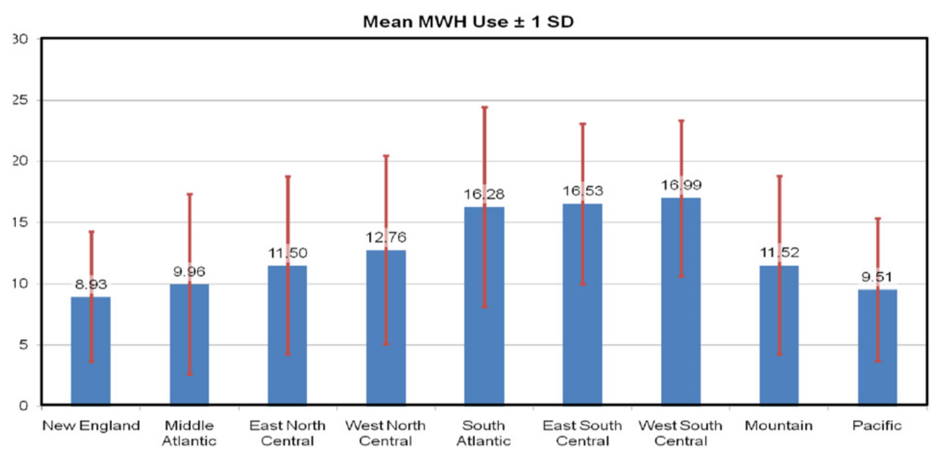

Fig. 1. Electricity usage in geographic regions sampled by RECS.

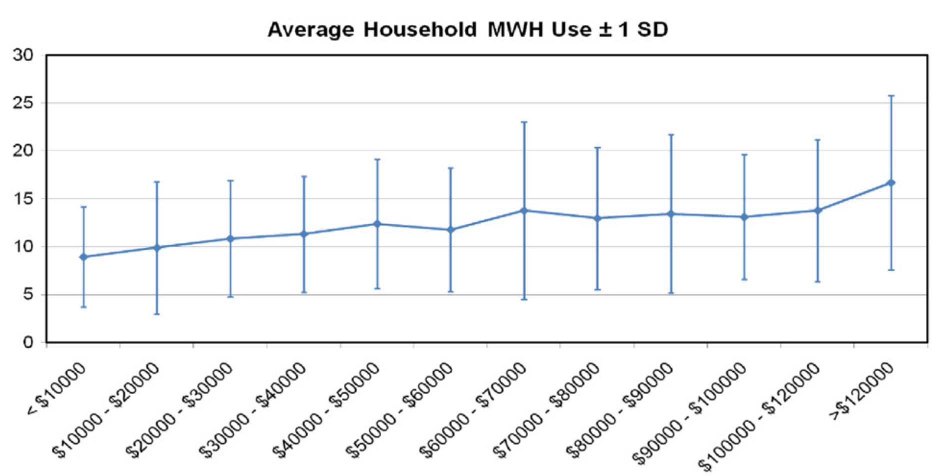

Fig. 2. Electricity usage and income for RECS respondents.

Table 2
Factor analysis of RECS variables with factor loadings contributing primarily to factor label and interpretation (Values in Bold).

Variables	Factors					Communality
	AC factor	Laundry factor	PC use factor	Climate factor	TV use factor	
Scaled air conditioning	**0.95**	0.07	0.08	0.15	−0.03	0.94
Natural log of total cooled square feet	**0.84**	0.08	0.05	0.09	0.03	0.73
Clothes dryer use, electric	0.08	**0.83**	0.05	0.04	0.07	0.70
Clothes washer use	0.03	**0.73**	0.13	−0.02	0.26	0.62
Number PCs	0.06	0.08	**0.87**	−0.01	0.04	0.76
PC time on total, weekly	0.06	0.07	**0.56**	0.02	0.04	0.33
Cooling degree days	0.26	−0.01	−0.07	**0.94**	0.03	0.95
Heating degree days	−0.05	0.06	−0.02	−**0.72**	−0.07	0.53
Number TVs	0.15	0.12	0.29	0.01	**0.53**	0.40
Number household members	−0.04	0.35	0.22	0.02	**0.43**	0.35
TV use	−0.01	0.10	−0.05	0.08	0.35	0.14
Number ceiling fans	0.27	0.09	0.14	0.26	0.13	0.18
Dish washer use	0.18	0.31	0.33	−0.07	0.14	0.26
Hours per day light bulbs are on	0.10	0.14	0.24	0.02	0.17	0.12
Oven use, electric	0.10	0.25	0.07	−0.03	0.09	0.08
Age of house	−0.23	−0.12	−0.18	−0.13	−0.04	0.12
LNKWH	0.39	0.35	0.32	0.20	0.26	0.49

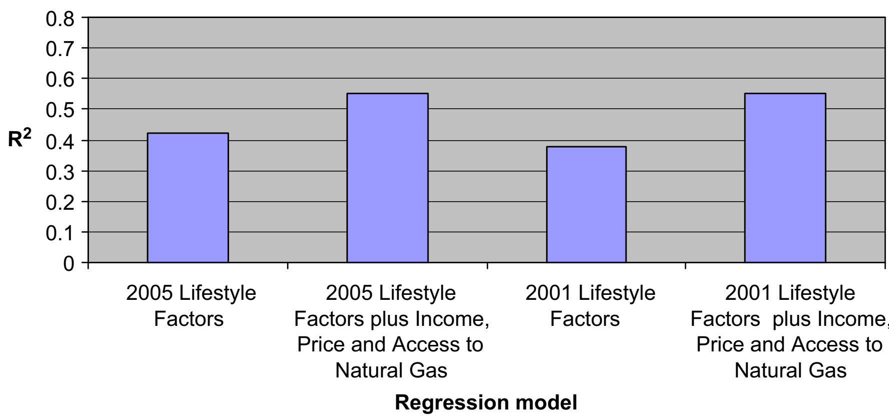

Fig. 3. R^2 results for four multiple regression models predicting electricity usage from lifestyle factors and other household variables.

loadings (i.e., correlations between lifestyle variables and the respective factor). For example, the Air Conditioning (AC) Factor has prominent loadings of 0.95 for Scaled Air Conditioning, and 0.84 for Ln Total Cooled Square Feet. Similarly, the second factor has prominent loadings with Clothes Dryer Use-Electric (0.83) and Clothes Washer Use (0.73). In turn, the third PC Use Factor has prominent loadings with Number of PCs (0.87) and PC on Total Weekly (0.56). Likewise, the fourth Climate Factor shows high loadings with Cooling Degree Days (0.94) and Heating Degree Days (−0.72). Finally the fifth TV Use Factor has >0.40 loadings with Number TVs (0.53) and Number Household Members (0.43); the marginal loading with TV Use (0.35) would seem to add to its definition. It is noteworthy that (a) each of the five factors has a significant loading with LNKWH and (b) they collectively are associated with about half of its total variation as shown by the communality in Table 2 (48.9%).

Analysis of factor scale score variance–covariance and correlation matrices indicated that the cross-correlations between the five scales tend to be small, with all but one are below 0.10 (the exception is 0.18 between the Laundry and TV Use factors). Additionally, the factor scale reliabilities, given by the covariance, indicate respectable degrees of statistical reliability. The reliabilities of the respective lifestyle factor-scales are 0.94 for AC, 0.77 for Laundry, 0.79 for PC Use, 0.94 for Climate, and 0.47 for TV Use.

4.3. Multiple regression results

Regression analyses were used to evaluate the utility of the lifestyle and household characteristics variables for predicting electricity usage. Four separate models were evaluated, including (1) the 2005 lifestyle factors, (2) the 2005 lifestyle factors plus income, price, and access to natural gas, (3) the 2001 lifestyle factors (predicted from the 2005 results), and (4) the 2001 lifestyle factors plus income, price, and access to natural gas. R^2 for each of these models is plotted in Fig. 3, and the results are discussed in the following sections.

4.3.1. 2005 Results

Regression analysis revealed a very substantial and highly significant relationship between the 2005 lifestyle scale scores and energy use: LNKWH-2005 ($\boldsymbol{R}(5, 2159)=0.65$, $\boldsymbol{p}<10^{-15}$)[3] . The R^2 of 0.42 shown in Fig. 3 corresponds to the proportion of LNKWH-2005 variance accounted for by the model. The adjusted R^2, i.e., the

[3] The parenthetical numbers, following convention, correspond to the degrees of freedom for the associated F-test for statistical significance of the multiple regression value **R**, describing the degree of association between the factor scores and energy use. The probability (p) value reflects the likelihood of obtaining the result by chance (Anderson, 2003).

proportion expected if the resultant model were fit to other samples from the same year, is identical.

Regression analysis revealed an even more substantial and significant relationship with LNKWH-2005 when the three household characteristic variables were combined with the five lifestyle variables ($\boldsymbol{R}(8, 2156)=0.74$, $\boldsymbol{p}<10^{-20}$), $R^2=0.55$. The three household characteristic variables—Ln-Income, Natural Gas Available, and Ln-Price—contributed an increase in the proportion of variance accounted over the lifestyle model of 0.131 ($\boldsymbol{p}<10^{-10}$); this added proportion is the difference between combined and lifestyle only R^2.

4.3.2. 2001 Results

Regression analysis revealed a very substantial and highly significant relationship between the 2001 lifestyle scale scores and energy use: LNKWH-2001 ($\boldsymbol{R}(5, 2678)=0.62$, $\boldsymbol{p}<10^{-15}$). Paralleling earlier results, R^2 corresponds to the proportion of LNWKWH-2001 variance accounted for by the model. This initial 2001 lifestyle result—given the reduction in the TV Factor reliability—is both remarkable in its similarity with that seen for 2005 (e.g., $R^2=0.38$ vs. 0.42).

Regression analysis showed an even more substantial and significant relationship with LNKWH-2001 when the three household characteristic variables were combined with the five lifestyle variables ($\boldsymbol{R}(8, 2678=0.74$, $\boldsymbol{p}<10^{-20}$). These three variables contributed an increase in the proportion of variance accounted over the lifestyle model of 0.171 ($\boldsymbol{p}<10^{-10}$). Remarkably, these 2001 lifestyle-combined results are identical with those seen for 2005 in several regards (cf. Fig. 3; $R^2=0.55$ in both cases).

Table 3
Regression coefficients for 2005 and 2001 models with lifestyle factors and household characteristic predictor variables.

Model variables	Unstandardized B coefficients		Standardized beta coefficients	
	2005	2001	2005	2001
Constant	6.94	7.03		
Lifestyle factors				
AC	0.19	0.18	0.29	0.26
Laundry	0.14	0.16	0.20	0.24
PC use	0.16	0.17	0.23	0.18
Climate	0.14	0.11	0.21	0.19
TV use	0.19	0.20	0.21	0.20
Household characteristics				
Ln price/KWH	−0.70	−0.79	−0.32	−0.37
Natural gas available	−0.29	−0.30	−0.20	−0.21
Ln income	0.08	0.05	0.11	0.07

4.3.3. Regression model coefficients

Table 3 presents the coefficient results for the regression models summarized in the previous sections. This table permits a comparison of the regression weights for the two different time periods: 2001 and 2005. The *B* coefficients, after the initial additive constant, are the respective weights that would be applied to the variables in the first column of the table in predicting an associated user value of LNKWH-2005 or 2001. *B* coefficients are expressed in the original units of measurement, whereas Beta-weights are standardized and dimensionless, and are akin to correlation coefficients; the square of the Beta-weight relates to the proportion of variance explained (Tabachnick and Fidell, 2007).

The five lifestyle factor variables can be seen to be associated with moderate positive *B*-weight contributions to the prediction of LNKWH-2005 and 2001, which were significant by the *t*-test ($P<0.0005$). Natural Gas Available and Ln-Price (KWH) both have significant ($P<0.0005$) negative *B*-weights, with the latter having both the largest individual *B* and Beta-weights. The log (Ln)-Income, although statistically significant, contrasts with earlier variables with both small *B* and Beta weights. The Beta weights (0.11, 0.07) signal a unique contribution less than half of that of the smallest value of the other variables in the model. Inclusion or exclusion of Ln-Income from the regression model changes R^2 by less than 1%. This result was consistent with the hypothesis that the lifestyle factors would account for the portion of Ln-income that was related to LNKWH.

The 2001 B-weights closely parallel those seen for 2005. Indeed, only the 2001 *B*-weight for Ln-Price (−0.79) is significantly different from the corresponding value (−0.70) in 2005 ($Z=2.103$; $p<0.04$, 2-tailed). Most remarkable is the consistency of the 2001 results when compared to those for 2005—this consistency promises similar utilities for the lifestyle and lifestyle-plus household characteristic models in analyses of comparable data from future RECS.

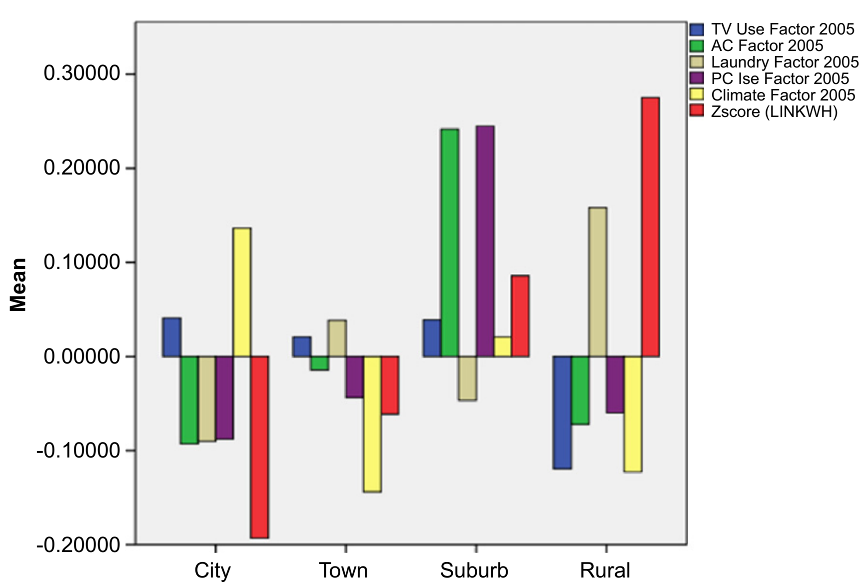

Fig. 4. Factor scores and standard values for annual electricity consumption for urban vs. rural locations sampled by RECS 2005.

4.4. Lifestyle factor segmentation

It is possible to use the lifestyle factors, in conjunction with electricity consumption data, to examine relationships between factor score groups and consumption patterns. Fig. 4 illustrates data segmenting the 2005 lifestyle factors on the basis of urban–rural location. This figure portrays some relatively clear relationships between location of the residence, electricity consumption, and various lifestyle factors from the RECS data. All differences discussed are significant at the 95% confidence level by Analysis of Variance and the Least Significant Difference Test for comparison of individual means.

City dwellers tend to be the lowest consumers of electricity, despite relatively hot climates (higher factor scores are associated with more cooling degree days). This appears to be due to lower levels of air conditioning square footage/usage reflected in the AC factor scores, in conjunction with lower scores on the Laundry and PC use factors. Town dwellers are similarly low in electricity consumption, show an opposite climate pattern to city households (colder), and show somewhat higher Laundry factor scores. Suburban homes represent a very clear cluster based on the Air Conditioning and PC use factors, but with relatively modest electricity consumption and a mild climate.

Rural households are clearly the largest consumers of electricity, despite relatively low scores on the Air Conditioning factor, and low scores on other factors. The rural households do have a significantly higher score on the Laundry factor, which is associated with more frequent usage of electrical appliances such as washers, dryers, and (to a smaller extent) dishwashers. The higher number of heating degree days for rural households may also impose additional electric fan load from the furnace, and there is a higher preponderance of electricity as the primary fuel for space heating (27% of households, vs. 21%, 16%, and 17% for city, town, and suburb, respectively).

Data from the 2001 RECS shows substantially similar results to those illustrated in Fig. 4, whether using factor scores estimated via the 2005 regression coefficients, or through the use of a ULS factor structure resulting from the analysis of 2001 data.

5. Discussion

5.1. Review and interpretation of results

The most noteworthy aspect of this analysis is the large proportion of variance in electricity consumption (42%) accounted for by the factors reflecting lifestyle patterns. These factors have relatively little to do with the physical shell of the residence, but instead portray social and behavioral predispositions and usage variation. The current work extends our understanding of the underlying patterns of consumption associated with socio-demographic variables, such as housing size, number of household members, and income (e.g., Gram-Hanssen et al., 2004; Poortinga et al., 2004; Diamond and Moezzi, 2004; Abrahamse and Steg, 2009). Factor analysis incorporates the variability in electricity usage associated with socio-demographic parameters, and thus can enrich our understanding of how and why electricity is consumed.

The five lifestyle factor structure obtained in this study reveals that the air conditioning factor accounts for the largest proportion of variance in electricity usage. This factor is composed of the correlated variables of air conditioning intensity (none, wall, central or both) and cooled square footage. Gram-Hanssen et al. (2004) have reported that housing square footage predicts the largest proportion of variance in Danish electricity consumption. The present results confirm a relationship with housing square footage, but provide elaboration by indicating that the energy service used in the living space is an important element. More detailed aspects of consumption in the living space, such as cooling, can be taken into account with the data available from the RECS survey. The large contrast between average the U.S. and Danish electricity usage (12237 kWh vs. 4189 kWh) suggests that there are differences in underlying cultural and usage patterns.

Additional insights regarding lifestyle are provided by the four other factors and their underlying measures. The laundry factor corresponds to a necessary end use, which has been shown in other studies to comprise a significant element of consumption (Gram-Hanssen et al., 2004). This factor is based primarily on variability in washer and dryer use, but also shows a modest relationship with the number of household members, as it may be expected that larger households would have more frequent laundering needs. The PC use factor is particularly interesting in that exploratory analysis showed income to be most highly correlated with this factor, suggesting that home information technology and electronics usage may be a manifestation of higher disposable income. When income is evaluated as an independent predictor and other lifestyle elements are accounted for through the factor structure, it adds less than 1% to the prediction of electricity usage.

The change in the magnitude of the regression coefficient for the PC use factor between 2001 and 2005, while not statistically significant, suggests a trend toward increasing electronics usage, which is also seen in other countries; Denmark, for example, shows an increase of 6% in PC electricity usage between 1999 and 2008 (Danish Energy Association, 2009, p. 20). Another indicator in this regard is the TV use factor, which is composed of the underlying measures of the number of televisions and the number of household members, and suggests a tendency for larger households to own and use more televisions. This is likely a reflection of increasing electronic proliferation as well, which is growing to be a significant end use (Energy Information Administration, 2011; Røpke et al., 2010). Subsequent versions of the RECS survey will contain more detailed items concerning re-chargeable electronic devices to facilitate assessment of this trend.

The climate factor measures the impact of region of residence upon electricity consumption that is independent of the air conditioning factor. The emergence of an independent factor based on cooling and heating degree days would seem to indicate that electricity consumption in warmer areas of the country may be higher regardless of air conditioning usage. A potential reason for this is that warmer regions tend to have newer residential developments that incorporate more small electrical loads such as outdoor lighting and pool pumps, which are not currently captured in the survey database.

Lifestyle factors appear to account for the correlated variable of household income, and thus better describe how that income is *consumed*. Previous studies showing relationships between income and *measured* electricity or energy consumption (Gram-Hanssen et al., 2004) indicated that income accounts for at most 6% of the variance in consumption. Other analyses (Kaza, 2010; Ndaiye and Gabriel, 2011) suggest that the effects are small and confined to the lower end of the income spectrum. Our findings show that income in and of itself is not a particularly good predictor of energy consumption, but instead overlaps with patterns of consumption that are better measured by other variables.

Of particular interest in this analysis is the cross-year stability of the factor structure in predicting energy consumption, indicating generality of the model. Tests involving eleven additional structural variables added to the various regression equations (such as physical shell material, ownership of multiple refrigerators, etc.) contributed only marginally to explained variance, and were not stable across time. Additionally, the significant difference in the regression weight for KWH price between 2001 and 2005 appears to be related to the price increase in electricity observed during the 2001 period (preceded by nearly 20 years of declining real prices), and the Western Energy crisis due to power shortages in certain markets. Thus, time-based analysis may be useful in evaluating temporal consumption elasticities, but price is not a major predictor in same-year models when contrasted with lifestyle predictors.

The results obtained in the present study illustrate the utility of factor analysis for constructing composite variables composed of multiple correlated measures. This analytic approach is based on creating independent predictors that enrich the explanatory power of individual measures. Further factor analytic work with properly scaled physical shell variables, such as insulation, glazing and building materials may further increase the predictive power of the models. Most of these data are not currently encoded as *interval* variables, but rather are *categorical* (i.e., ‘‘yes’’ or ‘‘no’’ or multiple categories, e.g., building material type), which makes them less amenable to classical factor analysis. Indeed, artificial factors would be extracted simply on the basis of negative correlations that structurally exist between categorical variables (Harman, 1976). Scaling these data as interval variables, as we have done with air conditioning intensity, would facilitate analyses of the physical building characteristics.

Segmentation of the data based on urban–rural location reveals patterns that contribute additional understanding of consumption across the census divisions and climate zones of the U.S. The high levels of air conditioning space and usage in suburban households suggest that new developments should either aim to increase efficiency or reduce usage through passive cooling. Shove (2003) has pointed out how building practices have co-evolved with the development of mechanical cooling; there has also been substantial retrofitting with air conditioning in the U.S. in the past 35 years with overall growth rates exceeding 100% (U.S. Energy Information Administration, 2005). Similarly, the high scores on the PC use factor for suburban households indicate that technologies and strategies for managing miscellaneous electricity loads would be beneficial.

The data for urban and town households present a different pattern of consumption and lifestyle factor scores, indicating that higher density and smaller living spaces are associated with reduced electricity consumption, regardless of climate zone (urban and town households appear to be differentially distributed between warmer and colder climates, respectively). The underlying lifestyle factors reflecting this are lower scores on the air conditioning, laundry use and PC use factors. The laundry and appliance usage scores do not appear to be driven by lower average household size or proportion of single occupant homes; analysis of average household size indicates that only the rural households differ statistically in that they have fewer household members. City dwellers may rely more on external services, including laundry, and spend less time in the home, which would also reduce PC usage. Rural electricity consumption is higher, and while the data do not clearly identify the underlying reasons for this finding, lack of household access to natural gas is a likely element. The higher laundry usage score for rural dwellers does not appear to be related to household size, as the average number of household members in rural settings is smaller. Instead, this may reflect a lifestyle consumption element of spending more time in activities requiring more frequent washings, such as outdoor tasks, or less usage of external services that are available to city dwellers.

5.2. *Lifestyle consumption analysis and policy implications*

Many aspects of lifestyle, such as region of residence, size of house, use ofair conditioning, how much information technology to have, and size of family and corresponding appliance usages, are socially developed and reinforced by the complex context in which everyday life takes place (Wilhite and Lutzenhiser, 1999). Policies implemented by federal governments often create the conditions that facilitate development and sustainment of various lifestyle choices, such as post-World War II suburbanization (Freund, 2006), and the energy consumption patterns associated with them. While social science provides considerable analytic discourse concerning these policies, there is much less impact on development and implementation of energy and climate policies (Shove, 2010). However, by understanding the patterns of energy consumption associated with lifestyle factors reflecting social and behavioral variation, it may be possible to develop more tailored policy interventions that go beyond the ‘‘nudges and wedges’’ of economic and information-based campaigns (Thaler and Sunstein, 2008; Dietz et al., 2009). Nudges refer to guiding consumer actions toward desired choices, such as requiring ‘‘opt out’’ for normative utility billing, for example. Wedges are behavioral actions, which, if taken, would reduce carbon emissions by a certain amount determined by modeling. Examples include replacing lighting with compact fluorescent bulbs, carpooling, and lowering thermostat settings.

Shove (2010) points to the limits of the ‘‘attitude, behavior, and choice’’ (ABC) model implied by such approaches, and suggests that government policies based upon it sustain current forms of consumption. The general mechanism of this model entails individual attitudes (A) driving behavior (B) that people choose (C) to engage in. The ABC approach to energy conservation rests fundamentally on the notion that individual behavioral choice will be the principal driver of reducing consumption, which heretofore has not been shown to be particularly effective either in terms of size of efficiency and conservation effects, or in the persistence of those effects.

This section discusses the implications of lifestyle-based energy research in the context of selected policy and intervention approaches aimed at reducing residential energy consumption, including information-based marketing, home energy audits and retrofits, billing and technical consumption feedback, and smart-grid approaches such as dynamic pricing and time-of-use electric rates. These approaches are discussed in recent U.S. policy documents, and represent current thinking about policy methods to manage electricity consumption (U.S. Department of Energy, 2009; Federal Energy Regulatory Commission, 2009; White House, 2010).

The current policy and intervention approaches listed above are framed within the context of the ABC model, and involve ‘‘nudges’’ toward reduced consumption via economic means, and ‘‘wedges’’ of efficiency based on energy audits, for example. As such, they operate to create marginal changes in current levels of consumption, rather than addressing the core element of energy use. In the subsequent section we discuss alternative approaches that rely less on the individual choices implied by the ABC model, and more on ‘‘upstream’’ or system-level policies that would create an ‘‘envirogenic’’ approach to lifestyle and energy usage (Shove, 2010) to address the broader context that establishes and maintains current levels of consumption. Lifestyle analysis can be used to portray variability within established systems of providing electricity to the residence, and help frame alternatives to the external constraints and influences that shape consumption (Moezzi and Lutzenhiser, 2010).

5.2.1. *Individual choice policies and interventions*

The marketing perspective of lifestyle research would appear initially to have relevance to information campaigns aimed at various lifestyle/energy consumption categories. Utility companies and third party billing processors are beginning to provide tailored energy reduction recommendations to residential consumers based on the analysis of household consumption patterns (Corcoran, 2010). However, considerable research has indicated the low impact of simple mass information appeals (Gardner and Stern, 2002). In a similar vein, home energy audits and financial assistance with efficiency upgrades are beginning to be seen again, in a re-play of approaches used in the late 1970s and 1980s (White House, 2009). A detailed review of these programs conducted by Walker et al. (1985) concluded that they should be considered marginally effective at best, with a total impact of 0.2% reduction in energy use after 5 years of operation.These programs appeared to be selectively adopted by households with higher incomes and orientations toward conservation (Hirst et al., 1981)

Both mass marketing and the provision of information and incentives through audits are based on the ABC model elements of individual behavioral choice. Analysis of home remodeling and energy retrofit efforts by Wilson and Dowlatabadi (in press) suggest that these programs are based on flawed ideas about why people remodel their homes; rather than efficiency upgrades, most people remodel to improve comfort, esthetics, and convenience. The definition of these latter elements changes with time (Shove, 2003), and may result in higher energy consumption due to additional convenience devices. Wilson and Dowlatabadi (in press) suggest that upstream intervention in the residential remodeling supply chain may be a more effective means of implementing efficiency upgrades than relying on the individual consumer to make the best energy-related choices. Lifestyle analysis of consumption can serve as an information source for understanding various segments, their patterns of energy usage, and potential points of influence in the supply chain beyond simple information appeals and modest incentives for the end user.

Another intervention technique that is influencing current approaches to policy development involves providing energy consumption feedback to residential consumers, either through billing (Allcott and Mullainathan, 2010) or through technical display devices in the home. Early studies conducted by Kohlenberg et al. (1976) used feedback and rewards to reduce energy consumption, and to specifically reduce or shift load peaking. It was shown that load peaking could be reduced by up to 50%, but the greatest difficulty in load shifting was associated with routines that used hot water and cooking. This early study established the precedent that electricity consumption **can** be altered with behavioral or usage feedback, but also illustrated the difficulties in altering patterns of consumption are well established and linked to daily comfort and convenience.

Parker et al. (2010) provide analysis indicating that the persistent effects of feedback systems are negligible, and suggest that home energy management/feedback systems may be best targeted at high consuming households that are financially motivated to change. In this way, such systems may eventually serve a role in consumer engagement with dynamic pricing systems implemented by utilities. Lifestyle-based consumption analysis can facilitate the definition of those households most likely to benefit from this approach, and for defining specific home energy management feedback categories.

Time-of-use rate and dynamic pricing can be combined with in-home displays to promote energy management (Faruqui et al., 2010). The conservation effect of the in-home display is approximately a 7% reduction, compared with smaller effects from dynamic pricing alone, although some studies seem to suggest that in-home displays can increase the impact of dynamic pricing. Similarly, in-home displays in systems involving pre-payment also show larger savings. Other studies have shown *load shifting* associated with critical peak pricing and prior notification (e.g., Herter and Wayland, 2010), but there seems to be an anticipatory increase in electricity consumption prior to the critical event, as well as a *post-event increase* in the 24 h period following the event. An interesting aspect of the Herter and Wayland (2010) study was the finding that higher income households showed the greatest percentage of load shifting, suggesting an inherently higher "spare capacity" for demand reduction. Further analysis of lifestyle patterns specific to these consumption profiles may be useful in targeting dynamic pricing and load control programs.

5.2.2. Beyond individual choices

The influence of the ABC model results in a "template for intervention which locates citizens as consumers and decision makers and which positions governments and other institutions as enablers whose role is to induce people to make pro-environmental decisions," (Shove, 2010, p. 1280). Other researchers have similarly commented on the dominance of the physical–technical–economic model (PTEM) (Lutzenhiser, 1993), and the potential for self-deception in energy policy resulting from this view (Wilhite and Norgard, 2003). The lifestyle consumption research approach reported here can serve as a bridge between individually oriented frameworks and policies, and a more holistic view of the role larger systems, including the mutually reinforcing relationships among government, suppliers, and consumers (Parag and Darby, 2009). A fundamental difference between the work reported here and traditional lifestyle marketing research is our focus on actual energy consumption, as distinct from attitudes or non-energy consumer spending.

Lifestyle energy consumption research can serve as a practical bridge between individual and social models through the multivariate nature of the analysis. There is a tendency in energy-behavior research to quantify relationships based on a few key variables, such as household income, house size, family size, etc., perhaps because these are the only variables measured, or because of the underlying theoretical framework. The factor analytic approach provides an efficient data reduction method to address multiple correlated variables that can be used to define higher-level aggregate lifestyle constructs. Variability in these factors, their socio-demographics, and how they change over time reflect specific patterns of consumption that can help understand changing standards of comfort and convenience (Shove, 2003), and can broaden policy strategies to include outside influences, infrastructure, and how they interact with daily life (Moezzi and Lutzenhiser, 2010; Shove, 2010). Outside influences include, for example, the increasingly inventive consumer electronics industry leading to higher levels of comfort and convenience devices (and more power consumption), which our results show in higher proportions in suburban locations. Is this because of higher incomes generally, more work at home, the suburban built environment, or combinations of these? The multivariate approach combined with segmentation analysis illuminates patterns of consumption and, potentially, their social origins (Moezzi and Lutzenhiser, 2010). Lifestyle analysis thus treats energy consumption as a set of "behavioral practices, situated in time and space," rather than focusing on individual attitudes or norms (Spaargaren, 2003).

Policies and interventions aimed at addressing broader societal levels of energy consumption are less in number and more aspirational than those based on individual choice. For example, renewable portfolio standards are being implemented at state levels in the U.S., and represent a supply-side approach to carbon reduction. For most residential consumers, the nature of the supply is either invisible or of little interest, and will remain so unless appropriate information and consumer engagement with the supply system is made possible through smart grid and home energy management systems. Lifestyle energy consumption analysis may eventually be useful in assisting utilities in determining load profile clusters based on usage patterns, and facilitate programs of gradual load shifting for use of greener power. Current mismatches between wind power availability and peak loads result in unused supply.

Progressive efficiency is a policy concept (Harris et al., 2008) that involves scaling efficiency requirements to the level of energy service used. In essence, larger homes, appliances, vehicles, etc., should be more efficient than smaller versions that use less energy. Calwell (2010) suggests that the increasing size and power consumption of televisions represent a near-term opportunity for development and implementation of progressive efficiency standards. The findings from our lifestyle consumption analysis indicate that electronics are associated with distinct patterns of consumption, and may therefore be useful in focusing the development and application of progressive efficiency in specific classes of consumer electronics.

Absolute energy consumption limits beyond a certain device size or service level are considered *sufficiency* criteria. Sufficiency policy concepts are likely to be controversial, implying as they do quotas and limits. They are also associated with a clear normative and moral element (Darby, 2007) that contrasts considerably with the model of individual choice and autonomy implied by the ABC model. Lifestyle analysis can be of value in addressing questions of sufficiency, based on the ability to capture the multivariate aspects of energy consumption, and to illustrate the wide energy use variability in achieving similar levels of service, such as comfort and convenience. Linkages to individual choice models can occur through definition of goals or desired normative consumption patterns that are provided to consumers through billing feedback, or graduated rate structures.

This brief discussion of policy approaches that are broader than those focused on individual choice interventions such as information or localized technical feedback illustrates the challenges of addressing the complex social structure of energy consumption. Recent policy analysis workshops in the U.S. (American Academy of Arts and Sciences, 2011) have shown the disparity between political feasibility and economic desirability of various energy policies, and illustrate the need for "polycentric governance," i.e., simultaneous and harmonized policies at federal, state, and local levels. Social science can provide useful inputs to this process, as illustrated by the success of the Hood River Conservation program (Hirst, 1987), which incorporated a sociological assessment to facilitate socially based dissemination pathways. More recent examples include Denmark's electricity system which blends community-level control with centralized national standards, and Germany's feed-in-tariff systems which integrates residential and community energy producers with federal systems (American Academy of Arts and Sciences, 2011). There is also considerable discussion in the U.S. regarding "consumer outreach" in the promulgation of smart grid technologies, although this may be more akin to advocating a *fait accompli*.

6. Conclusions

This study has illustrated a factor analytic approach to lifestyle energy consumption research using data from the 2005 RECS. Five lifestyle factors account for more than 40% of the variance in electricity consumption, and provide independent measures of the influence of air conditioning usage, laundry usage, PC usage, television usage, and climate. Income adds negligibly to predictive power. We have shown that the lifestyle factors can be used to estimate prior-year consumption from similar survey data, and are stable over time. Segmentation analysis illustrates variable patterns of consumption associated with different urban and rural locations. Thus, the lifestyle factor analytic approach represents a means to enrich our understanding of the multivariate basis of residential electricity consumption, and energy consumption more generally. Policy intervention approaches at both the individual and social level can benefit from incorporating findings from lifestyle analyses, and the technique may serve as a useful bridge between individual and socially oriented models of consumption.

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