

Chapter 5

Household Energy Consumption Behavior

Biyang Yu and Junyi Zhang

Abstract This chapter deals with not only household car ownership and usage, but also ownership and usage of in-home electric and electronic appliances from the perspective of energy consumption. Household energy consumption is an outcome of a series of life choices including end-use ownership, end-use efficiency, end-use usage, time use, expenditure allocation, residential location choice, employment choice, and household structure decisions. It is related to all life domains and also has externalities such as impacts on health. Life-oriented methodology that considers the potential interactions between household energy consumption and other life choices would be more appropriate to investigate this issue. To that end, this chapter sheds light on three fundamental questions related to household energy consumption: (1) How much is the minimum energy demand for households in the context of their life choices? (2) How do factors of attitude, belief and consciousness work on residential choice and household energy consumption? (3) How can household energy demand be actively managed by designing life choice-oriented interdisciplinary policies? In this chapter, the externality of household energy use on health is discussed as well.

Keywords In-home and out-of-home energy consumption • Integrated behavior model • Energy demand management system • Waste energy • Re-bounce effects • Self-selection effects • Health

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5.1 Background

In recent years, great progress has been made to slow down and stop the pace of climate change. Indeed, good signs have been seen that economic growth and energy-related emissions, which have historically moved synchronously, are starting to decouple. The energy intensity of the global economy continued to decline in 2014 despite economic growth of over 3 %. However, increasing effort is still needed if we are aiming to limit the rise in global mean temperature to 2 °C (IEA 2015). To that end, efforts to develop cleaner and more efficient energy technologies should be further enhanced. Globally, the industrial final energy consumption fell by 4 % from 1973 to 2011 (Fig. 5.1). In addition, residential consumption accounted for about a quarter of global total final consumption. This share has remained stable over the last 35 years and is likely to remain more or less the same in the future in spite of technology change (IEA 2014), probably because of the contribution from the developing countries, whose shares are continuing to increase due to the unsaturation of domestic end uses as well as poor living conditions. For the transport sector, the total final energy consumption increased from 23 % in 1973 to 27 % in 2011 (IEA 2014), suggesting that energy savings from new efficient technologies are likely to be offset by increasing demand for transport.

Based on these statistics, it is not difficult to realize that, in contrast to industrial and service sectors, residential and private transport energy consumption requires more active controls in addition to technology improvement, because they are associated with the way individuals and households use energy to heat, cool, and light their homes, run an increasing number of electric appliances, and drive their cars. All forms of consumption are a result of life choices (e.g., end-use ownership, efficiency choice, end-use usage, time allocation, expenditure allocation, residential location choice, and job choice) and can be a form of self-expression (Hubacek et al. 2009; Schaffrin and Reibling 2015; Wei et al. 2007).

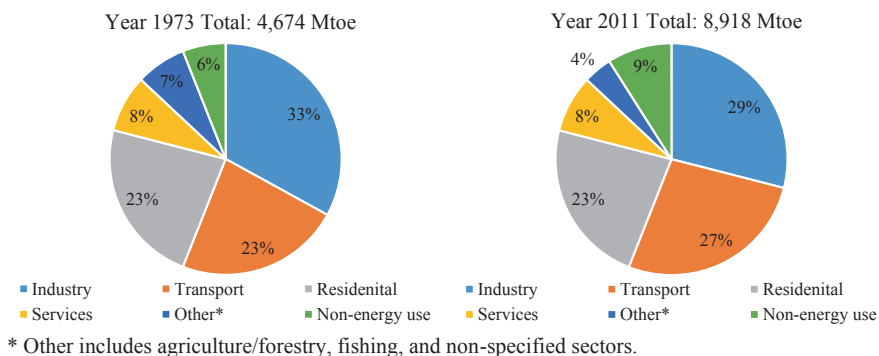


Fig. 5.1 Shares of sectors in total final consumption for the world (1973 and 2011) (IEA 2014)

In other words, determining how to achieve sustainability in these two sectors relies to a large extent on household/individual daily behavior in all life domains, which might be quite different across the population, making it more difficult to control through regulation than other energy-consuming sectors. The incentives for bundling residential consumption and private transport consumption together as household consumption have been demonstrated repeatedly in the literature (Yu et al. 2011, 2012, 2013a, b, c). Therefore, this chapter will depart from the context of a comprehensive household sector by including both residential and private transport sectors.

5.2 Energy Consumption, Life Choices, Quality of Life, and Environmental Consequences

Motivated or restrained by attitude, belief, and consciousness (ABC) factors, as well as sociodemographic and economic factors, people make a series of interrelated choices about their employment, residence, and family composition, which may further influence their other life choices, such as daily activities and monetary consumption. These life choices are further attributable to people's quality of life (Veenhoven 2014; Zhang and Xiong 2015). It is worth noting that self-selection effects (Cao et al. 2009; Mokhtarian and Cao 2008; Van Wee 2009) might exist between these choices (Zhang 2014). To support daily activities, households/individuals need to purchase the necessary goods and end uses (end-use ownership choice) with appropriate technologies (technology choice), and decide how long and how often to use them (end-use usage). In turn, this causes additional expenditure on goods, appliances, and/or vehicles. The activity pattern of a household/individual relates to the main driving forces of direct residential and passenger transport energy consumption, namely the duration of use of energy-consuming appliances, the number of trips taken to support daily activities, the mode of travel, and the timing of travel (Ellegård and Palm 2011; Widén et al. 2009). On the other hand, expenditure on goods and end uses will induce energy consumption during the life cycle of industrial production for materials or services (Bin and Dowlatabadi 2005; Wei et al. 2007). Consequently, the choices of activity pattern and expenditure may be further linked to energy consumption. In other words, household energy consumption is a result of all the aforementioned life choices, as shown in Fig. 5.2, and changing any one of them may have derivative effects on the others. Using data from 198 countries for the period 1990–2009, Al-mulali (2016) found that “energy consumption improves the life quality of 70 % of the countries despite their different incomes. ... the life quality indicators also increase energy consumption, a phenomenon that appears to be true in 65 % of the countries.” Thus, energy consumption and quality of life are interrelated.

The world still depends on fossil fuels that represent 81 % of total energy consumption (Al-Mulali 2016). The OECD extensively examined environmental pressure from households from the perspectives of waste generation and recycling,

personal transport choice, residential energy demand, environmentally responsible food choice, and residential water use (OECD 2008). It is predicted that environmental pressure from households will significantly increase by 2030: total residential energy use in OECD countries will increase by an average of 1.4 % per year from 2003 to 2030 and non-OECD residential energy use will be nearly 30 % higher than the OECD total in 2030 (Ferrara and Serret 2008). Zaman et al. (2016) confirmed the relationships between energy, environment, health, and wealth in BRICS countries (Brazil, Russia, India, China, and South Africa) over the period 1975–2013, and suggested that a carbon-free economy should be the priority for the green growth agenda that helps prevent environmental health hazards. More evidence of the negative effects of energy consumption on public health is seen in Wang (2010). On the other hand, Ellegård and Palm (2011) argued that policies reducing environmental loads from households must relate to and rely on individuals’ daily choices and household routines, i.e., what they do in their everyday lives.

Under the full picture in Fig. 5.2, this chapter sheds light on three fundamental questions related to household energy consumption. (1) How much is the

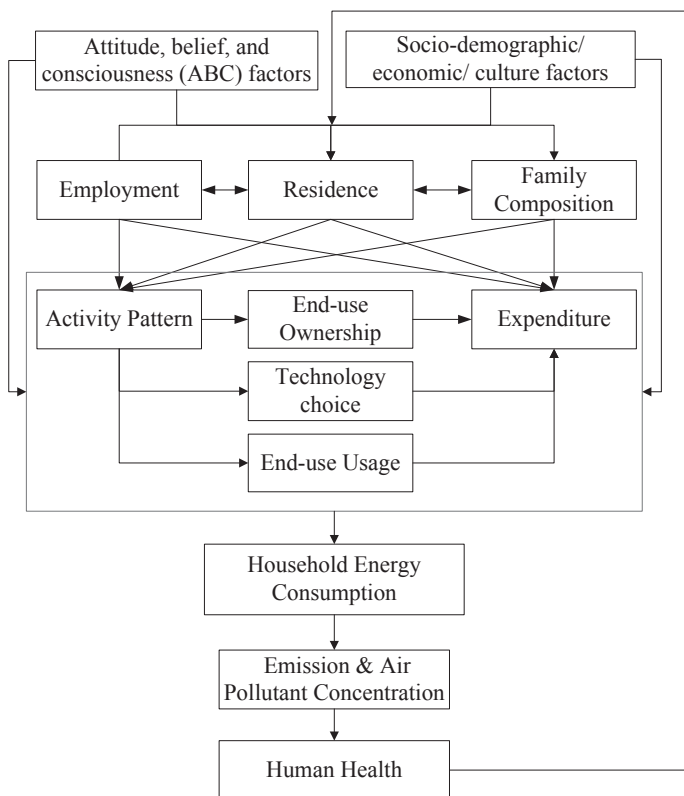


Fig. 5.2 Life choices and environmental consequences

minimum energy demand for households in the context of their life choices? (2) How do the ABC factors work on residential choice and household energy consumption? (3) How can household energy demand be actively managed by designing life choice-oriented interdisciplinary policies? As an extension, the externality of household energy use on health will be discussed through a review.

5.3 Household Energy Consumption, How Much Can Be Cut Down?

5.3.1 Behavioral Mechanism

Energy is an indispensable resource for household production and is consumed in meeting different needs in daily life (e.g., eating, showering, cooling and heating, entertainment, working, and so on). Energy consumption for meeting basic needs is not the same as that for meeting higher-order needs. The energy consumption for basic needs may not be significantly different between households if household composition and other attributes are the same, and there is probably no potential to cut down this part of consumption by external policies because the minimum quality of life should be ensured for each household. However, for higher-order needs, energy consumption across households with the same composition and attributes could differ significantly. Only for these needs might “unnecessary” consumption exist and be able to be reduced by policy instruments, along with the constraints of basic needs (Baxter et al. 1986; Schaffrin and Reibling 2015). The question of energy consumption for human basic needs immediately raises the issue of a minimum threshold energy budget; i.e., one above which human basic needs can reasonably be met. Filippini and Hunt (2012) estimated the underlying efficiency of residential energy consumption for each US state; substantial variation of efficiency was found between different states, suggesting that the phenomenon of “waste energy” is quite prevalent. Chung (2011) reviewed dozens of articles related to the benchmarking of buildings in light of energy-use performance (i.e., the lowest energy-use buildings), and the main methodologies [including Ordinary Least Squares (OLS), Stochastic Frontier Analysis (SFA), and Data Envelopment Analysis (DEA)] for dealing with energy efficiency were summarized and compared.

5.3.2 Case Study: Does “Waste Energy” Exist or Not?

In this section, based on an empirical study in the context of Beijing, we give an example of how to address the questions concerning whether “waste energy” exists or not and how much household energy consumption can be cut down. Stochastic frontier analysis (SFA) (Fernández et al. 2005) is applied to identify the end uses showing inefficient consumption in households, as well as the lower

bound of energy expenditure (minimum expenditure) for these end uses in each household. The data employed here are obtained from a household energy consumption survey conducted in Beijing in 2010 (Yu et al. 2015).

To analyze the inefficiency of end uses, the single-output nature SFA analysis with frontier cost function is conducted for each end use. It is unlikely that all households operate at the frontier with minimum consumption, and failure to attain the cost frontier implies the existence of consumption inefficiency. The part of consumption excluding the inefficient consumption equals the part for basic needs. The mathematical expression is denoted as:

$$\ln Y_{ij} = \beta \ln X_{ij} + u_{ij} + v_{ij}, \quad u_i \geq 0 \quad (i = 1, 2, \dots, N \text{ and } j = 1, 2, \dots, 9) \quad (5.1)$$

where i is household, j is end use, and X_{ij} is a group of variables representing the household/individual heterogeneity; the first error term u_{ij} is a one-sided nonnegative disturbance reflecting the inefficiency of end use j in household i , $u_{ij} \sim idN^+(0, \sigma_u^2)$; the second error term v_{ij} is a two-sided disturbance capturing the effect of measurement error and random factors, $v_{ij} \sim iidN(0, \sigma_v^2)$.

Inefficiency is indexed by the ratio of the actual costs (the actual energy expenditure) to the lowest cost level (the minimum energy expenditure):

$$\text{Inefficiency}_{ij} = \frac{(Y_{ij}|u_{ij}, X_{ij})}{(Y_{ij}|u_{ij} = 0, X_{ij})} = \frac{\beta \ln X_{ij} + u_{ij}}{\beta \ln X_{ij}} \geq 1 \quad (5.2)$$

The variables used to describe the cross-sectional heterogeneity in SFA are listed in Table 5.1. In total, nine durable end uses are targeted: refrigerators, electric fans, air conditioners (AC), gas showers, washing machines, TVs, PCs, microwave ovens, and private cars. The results in Table 5.2 and Fig. 5.3 show that for these nine end uses, only for the usage of refrigerators, washing machines, microwave ovens, and cars is there significant inefficient consumption. The inefficiency level of the domestic end uses (i.e., refrigerators, washing machines, and microwave ovens) ranges from 1 to 5, and almost 80 % of the sample is below 3. By contrast, the inefficiency level of cars is much wider (i.e., 1–19), indicating a

Table 5.1 Variables in the stochastic frontier analysis (SFA)

Variable	Description	
Y_{ij}	Energy consumption per person on end use j in household i	
$x_{ijm} (m = 1-7)$	x_{ij1}	Household annual income level
	x_{ij2}	Household size
	x_{ij3}	Accessibility to the nearest bus stop/MRT station
	x_{ij4}	Accessibility to the nearest supermarket
	x_{ij5}	Energy intensity of the end use
	x_{ij6}	Accessibility to the nearest shopping mall
	x_{ij7}	Accessibility to the nearest park
$\ln(x_{ijm}) * \ln(x_{ijn})$	$(m, n = 1-7, n \geq m)$ interacted terms between each two of the above seven x variables	

Table 5.2 Estimation results of SFA model

	Refrigerator	Fan	AC	Shower	Washer	TV	PC	Microwave oven	Car
ln x ₁	0.032	0.234	-0.035	-0.545	-0.867	-0.510	1.335	0.413	-0.119
ln x ₂	-0.163	-2.579	-0.722	0.773	-0.709	-1.439	-1.167	-1.650	-1.783
ln x ₃	0.336	-0.134	-0.011	0.251	-0.451	-1.421	0.783	0.239	3.382
ln x ₄	0.214	0.551	0.296	0.579	1.739	-0.144	-0.851	1.734	3.717
ln x ₅	-0.634	0.824	1.232	0.905	0.409	3.587	7.093	0.732	1.654
ln x ₆	-0.621	0.991	-0.470	-1.627	-0.417	-0.651	-0.441	4.065	-3.382
ln x ₇	0.146	-1.421	-0.969	-0.387	-0.458	0.699	0.516	-5.659	-2.456
ln x ₁ ln x ₁	0.044	-0.248	-0.022	-0.056	0.379	-0.034	-0.059	-0.154	0.114
ln x ₁ ln x ₂	-0.007	-0.126	-0.240	0.264	-0.007	0.321	0.068	0.479	-0.233
ln x ₁ ln x ₃	0.114	-0.183	0.102	0.276	0.046	-0.171	0.026	0.238	-0.372
ln x ₁ ln x ₄	-0.169	-0.026	-0.276	-0.518	-0.545	0.240	-0.180	-0.008	-0.787
ln x ₁ ln x ₅	0.017	-0.024	0.486	0.002	0.034	-0.009	-0.171	-0.058	0.102
ln x ₁ ln x ₆	0.089	0.078	0.313	0.369	0.112	-0.013	-0.110	-0.396	0.641
ln x ₁ ln x ₇	-0.055	0.217	0.111	0.285	0.313	0.120	0.029	0.370	0.372
ln x ₂ ln x ₂	0.014	0.321	0.280	-0.042	-0.169	0.076	0.209	-0.210	0.023
ln x ₂ ln x ₃	0.139	-0.208	-0.044	0.291	-0.033	0.137	-0.391	0.476	-0.078
ln x ₂ ln x ₄	0.008	-0.087	-0.040	-0.297	0.152	0.030	0.086	-0.464	0.019
ln x ₂ ln x ₅	0.139	0.286	-0.854	-0.569	-0.008	0.066	-0.040	0.103	0.780
ln x ₂ ln x ₆	-0.033	0.600	-0.049	0.171	0.105	0.178	0.221	0.131	0.175
ln x ₂ ln x ₇	0.029	0.018	0.310	-0.422	0.115	-0.312	-0.195	-0.161	-0.450
ln x ₃ ln x ₃	-0.069	-0.173	-0.137	0.332	-0.129	0.203	0.108	-0.310	-0.124
ln x ₃ ln x ₄	0.042	0.283	-0.239	-0.477	0.156	-0.025	-0.277	-0.288	0.279
ln x ₃ ln x ₅	0.089	-0.039	0.200	-0.321	0.078	0.212	-0.175	-0.260	-0.875
ln x ₃ ln x ₆	-0.019	-0.214	0.154	0.041	0.154	0.065	0.620	0.760	-0.488

(continued)

Table 5.2 (continued)

	Refrigerator	Fan	AC	Shower	Washer	TV	PC	Microwave oven	Car
ln x3 ln x7	0.031	0.700	0.104	-0.123	-0.042	-0.002	-0.160	0.405	-0.480
ln x4 ln x4	0.068	-0.462	0.123	0.229	-0.299	-0.202	0.029	0.303	-0.160
ln x4 ln x5	-0.016	0.065	-0.488	-0.037	-0.164	0.009	0.289	-0.141	-0.989
ln x4 ln x6	-0.154	0.226	-0.293	-0.155	0.020	0.365	-0.356	-0.062	-0.559
ln x4 ln x7	-0.069	-0.305	0.214	0.456	-0.281	-0.302	-0.053	-0.349	0.264
ln x5 ln x5	-0.099	0.008	-0.017	0.039	0.057	-0.254	-0.601	-0.007	-0.570
ln x5 ln x6	-0.063	-0.267	-0.064	0.625	-0.058	0.184	0.063	-0.566	0.907
ln x5 ln x7	0.003	0.175	0.330	0.030	-0.029	-0.089	-0.090	0.895	0.974
ln x6 ln x6	0.152	-0.076	0.395	0.147	0.299	-0.303	-0.027	0.432	0.933
ln x6 ln x7	0.086	-0.481	-0.273	-0.159	0.002	-0.097	-0.073	-0.360	-0.422
ln x7 ln x7	-0.107	0.414	0.299	0.164	0.149	0.195	0.140	-0.079	0.492
Intercept	4.829	0.314	5.914	3.360	0.538	-6.024	-15.02	-3.278	3.982
Lambda	1.608	0.732	1.272	1.437	1.453	0.029	0.031	0.991	2.630
Sigma2	0.288	0.707	0.873	0.866	0.905	0.375	0.604	1.633	0.961
R-square	0.726	0.816	0.622	0.651	0.737	0.994	0.996	0.846	0.873

Note Lambda = σ_u/σ_v , Sigma2 = $\sigma_u^2 + \sigma_v^2$. Bold and italic numbers mean significant at the 90 % level

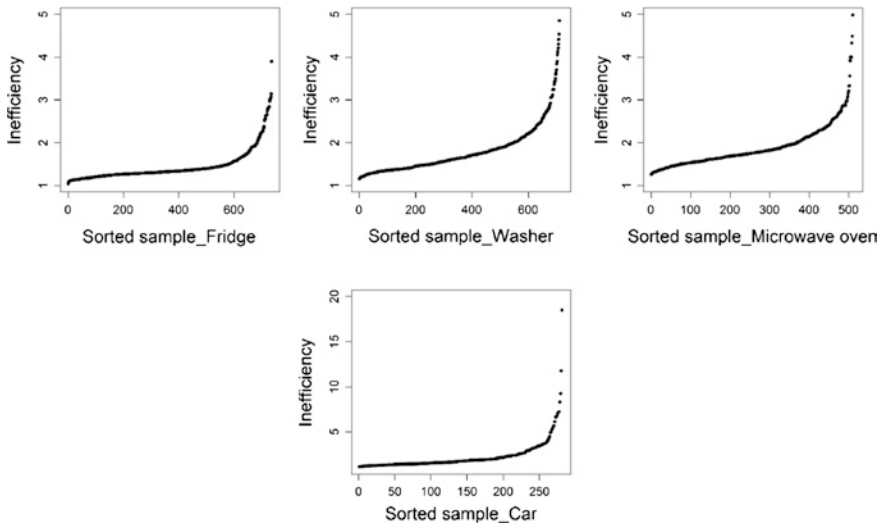


Fig. 5.3 Inefficiency level of the end uses (Yu et al. 2015)

substantial variance. It can be inferred that energy consumption for cars might be easier to control and the extent for reduction will also be broader than domestic end uses when the relevant policies [e.g., integrating persuasive technology with energy delegates (IPTED) (Emeakaroha et al. 2014), rumor propagation (Han et al. 2014), and eco-feedback systems (Jain et al. 2013)] are carried out. The minimum expenditure or the lower bound ($y_{ij} = \beta \ln X_{ij}$) of the end-use usage in each household can be further calculated and this limit is supposed to change with household/individual characteristics in future years.

5.3.3 Summary

The findings on inefficient consumption and the minimum threshold for households are enlightening because they contribute to target setting and the effectiveness of the climate policies that encourage the proenvironmental behavior of households. The results in the Beijing case study show that the demand for the service of electric fans, ACs, gas showers, washing machines, TVs, and PCs is to meet basic life needs, implying that the energy consumption on these five end uses is difficult to cut down by policies other than technology improvement. For the four end uses with inefficient consumption, it should be noted that irrespective of the policies carried out, there is always a maximum bound for energy saving.

Furthermore, considering life needs may change with the progress through life stages; decision-making patterns may or may not be transferred from one stage to the next stage(s). This issue should be investigated using panel approaches to capture the dynamic change of consumption for basic needs.

5.4 ABC Factors and Household Energy Consumption

5.4.1 Behavioral Mechanism

In relation to the need for energy in life, in addition to objective factors such as income and household composition, subjective factors such as attitude, belief, and consciousness (ABC) of different life activities may play a role in understanding household energy consumption behavior. The question whether environmental attitudes, beliefs, and consciousness result in proenvironmental behaviors with regard to energy conservation has been extensively studied (Abrahamse et al. 2005; Ohler and Billger 2014; Ozaki and Sevastyanova 2011). A growing body of research indicates that many people and households engage in proenvironmental actions (e.g., recycle their waste or sort garbage themselves (Czajkowski et al. 2014), and buy organic food or efficient appliances (Steg et al. 2014) with the consideration of benefiting other people, future generations, and the environment, even though these actions may be costly. These proenvironmental actions accordingly induce energy savings or emission reductions (Bolderdijk et al. 2013; Gadenne et al. 2011; Martinsson et al. 2011; Sapci and Considine 2014; Yu et al. 2011). Even though the targeted areas, the analysis methods, and the survey data used in these studies are quite varied, similar relationships between these psychological factors and energy consumption are identified. Consequently, it is plausible that changing such unobserved factors, e.g., ABC factors, by informational or educational campaigns could be an alternative means to reduce energy use for a proportion of households.

On the other hand, the subjective factors are usually the inherent characteristics of people, implying that they may impact two or multiple life choices and activities: extroverts may enjoy staying out and socializing more with others (less in-home energy use); car addicts may buy a car and become a heavier car user (more fuel consumption); workaholics may spend most of their time working and less time on other activities (more consumption on work-related activities); proenvironmentalists may buy high-efficiency appliances and take public transport (less energy consumption); and so on. Indeed, all of these subjective factors are related to household energy consumption behavior, suggesting that household energy consumption should be analyzed jointly with other life choices.

5.4.2 Case Study: Self-selection Effects Between Residential Location Choice and Household Energy Consumption Behavior

Residential location choice has a long-term influence on household energy consumption behavior, referring to end-use ownership and usage. Brand et al. (2013) found that urban/rural status, home-to-work distance, home-to-retail distance, and home location had a significant influence on energy consumption and carbon

dioxide emissions from motorized passenger travel in the UK. Nässén (2014) and Rahut et al. (2014) identified different domestic energy consumption patterns for rural and urban households in Sweden and Bhutan, respectively. In addition to the above causal effect from the residential environment (RE) characteristics to household energy consumption behavior, many researchers argue that there are other noncausal associations between these two dimensions derived from intervening variables that cause both. This relationship is called the “self-selection effect” (Mokhtarian and Cao 2008; Yu et al. 2012). Statistically, self-selection arises in any situation in which individuals select themselves into a group. The self-selection effect might come from ABC factors (Ohler and Billger 2014; Ozaki and Sevastyanova 2011), social factors such as lifestyle and life stage (Lutzenhiser 1993; Weber and Perrels 2000), and cultural factors (Abrahamse et al. 2005; Lutzenhiser 1992) among others. It is further argued that the self-selection effect might vary with life domains. For example, households that do not like cooking may choose to reside in a neighborhood with good catering facilities (e.g., restaurants and/or supermarkets), consequently, with fewer cooking-related end uses; households with a preference for driving may prefer to live in suburban areas to satisfy their desire to drive. Obviously, these two effects are distinct. This section introduces a case study that sheds light on household energy consumption behavior by incorporating multiple self-selection effects.

To that end, an integrated model, termed a mixed multinomial logit–multiple discrete-continuous extreme value (MNL–MDCEV) model, is built. This model covers residential location choice, end-use (including in-home appliances and out-of-home cars) ownership, and usage behavior, by considering a comprehensive set of RE and sociodemographic variables, as well as multiple self-selection effects. Bearing in mind the focus of this section, we only discuss the results related to the effect of unobserved factors (e.g., ABC factors) that cause self-selection effects on household energy consumption behavior; other results and conclusions can be found in Yu et al. (2012).

The MNL–MDCEV model includes the unobserved factors associated with both residential choice and household energy consumption behavior, which are regarded as the cause of multiple self-selection effects. To represent the sample heterogeneity, these factors are assumed to follow a normal distribution and Table 5.3 lists the estimation results of the mean and standard deviation for each end use. Based on the means, it was found that there is a significant unobserved component simultaneously affecting residential location choice and the ownership and usage of all end uses, indicating a correlation between long-term residential location choice behavior and medium/short-term household energy consumption behavior. In addition, the self-selection effects differ across end uses, verifying the need to incorporate multiple self-selection effects into the integrated model. Specifically, for in-home end uses (i.e., refrigerator, AC, electric shower, washing machine, TV, and PC), the positive self-selection effect indicates that some unobserved factors make households select themselves to a particular neighborhood and be more likely to own and spend more money on these end uses. For electric fan, gas shower, microwave oven, and car, the negative sign means that

Table 5.3 Unobserved factors related to self-selection effects

Unobserved factors	Fridge	Fan	AC	Electric shower	Gas shower	Clothes washer	TV	PC	Microwave oven	Car
Mean	6.663	-30.112	39.05	2.840	-2.637	8.764	8.189	5.608	-5.603	-9.826
s.d.	2.844	3.968	3.798	2.461	5.098	2.333	2.218	1.984	3.886	4.023

certain unobserved factors make households select themselves to some other particular neighborhood and be less likely to own these end uses or spend less money on them. For the standard deviations, it is confirmed that the multiple self-selection effects on the residential choice and energy consumption behavior of refrigerator, AC, electric shower, washing machine, TV, PC, and car vary significantly between households. Furthermore, these heterogeneous self-selection effects are more obvious for the ownership and usage of electric shower and car. This also supports the rationality of accommodating end-use-specific self-selection effects instead of using a common effect for all end uses. Although based on the model results, we cannot clarify what the self-selection effect exactly is or how to change it; however, after controlling for the self-selection effect in the model, the relatively true effect from residential environment variables can be captured, leading to less biased evaluation of land-use policy for household energy consumption.

To identify how much various factors influence household energy consumption behavior, we calculate the contribution ratio by each factor. For ease of interpretation, the total effects from three groups of variables are compared: household attributes (including household income, household size, presence of children and elders, number of workers and education level), residential environment attributes (including the CBD, suburban area, number of shopping malls, supermarkets, recreational facilities, restaurants, parks, bus lines and train lines in the neighborhood), unobserved factors only related to household energy consumption behavior, and unobserved factors associated with self-selection effects. It can be seen in Fig. 5.4 that different attributes have their own leading domain. Household and

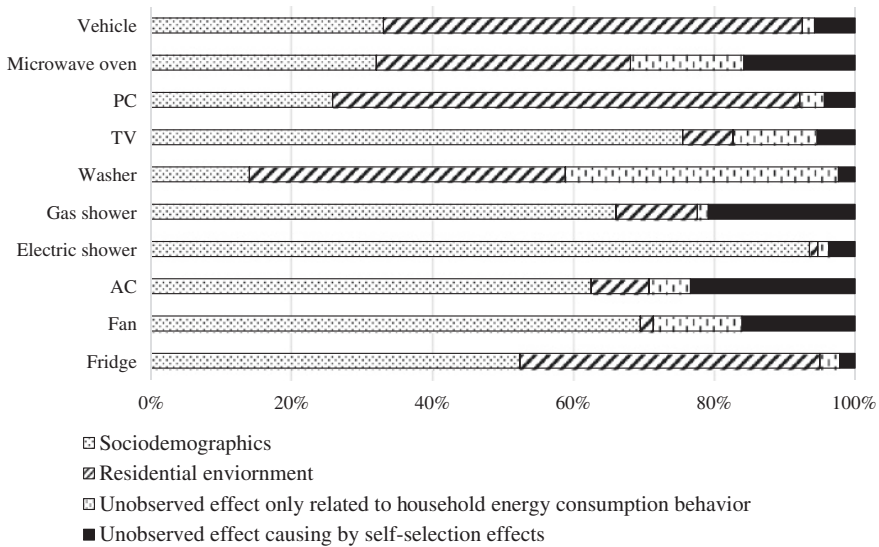


Fig. 5.4 Contribution of different attributes on household energy consumption behavior for end uses

individual attributes dominate for the energy consumption behavior of refrigerator, electric fan, AC, electric shower, gas shower, and TV. For washing machine, PC, microwave oven, and car, residential environment attributes play a more important role in explaining ownership and usage behavior. The contribution of unobserved factors varies greatly with end uses, ranging from 5 to 41 %, among which the portion causing self-selection effects varies from 2 to 24 %, suggesting a significant contribution that cannot be neglected when modeling the interaction between residential choice and household energy consumption behavior.

5.4.3 Summary

This section emphasizes the importance of considering the unobserved factors that influence household energy consumption behavior. The significant unobserved factors associated with the self-selection effects in the case study suggest that residential environment attributes are not completely exogenous in household energy consumption behavior. In other words, the effect of land-use policy on household energy use would be incorrectly estimated due to the existence of self-selection effects. This is an example showing the interaction between different life choices (i.e., residential location choice and household energy consumption decision choices) triggered by the subjective factors. As noted above, ABC factors are usually the inherent characteristics of people, meaning that besides the residential domain, there might be some other life domains interacting with household energy consumption due to ABC factors. Future analysis could start from this notion. In addition, in the case study, the self-selection effect was found to vary between 2 and 24 % with end uses. This validates the need to consider end-use-specific or life-choice-specific self-selection effects. The above finding strongly suggests that when planners attempt to develop interdisciplinary policy to save energy, in addition to the objective factors (e.g., RE attributes, sociodemographics, and housing attributes), the subjective factors (e.g., the ABC, social, and cultural factors) that might cause the self-selection phenomenon should also be introduced to understand energy consumption behavior. It is also implied that to conserve household energy consumption, it is important to introduce “soft policy”, such as the provision of information about energy-saving behavior and an evaluation platform for households to monitor their energy consumption and emissions.

The remaining issue is how to identify and quantify the exact effect of ABC factors to determine the appropriate policies. Some researchers ask about people’s environmental awareness or willingness to pay for environmentally improving measures (Tsushima et al. 2015; Wang et al. 2015); however, it is argued that those households that have positive environmental concerns and attitudes do not always consume less energy or do not recognize the relevance of energy savings (Gaspar and Antunes 2011; Holden and Linnerud 2010). Such inconsistencies should be taken into account. Panel surveys or field experiments might produce better data and the multilevel model could be an alternative method to stratify ABC factors.

5.5 Interdisciplinary Policy Scheme

5.5.1 Behavioral Mechanism

To achieve sustainable energy demand management, it is important to design a proper policy scheme to combine the effects of new technology, awareness campaigns, social norms, city structure, and comparative information (Khansari et al. 2014); in other words, a series of interdisciplinary countermeasures should be designed and carried out at the same time or successively put into practice. Accordingly, evaluating the collective effect of these countermeasures on household energy demand via an examination of the behavior change becomes the crucial challenge. Gomi et al. (2011) highlighted three types of relationships between policies: (1) policies that have an accelerating effect on other policies; (2) policies that are the prerequisite policies for others; and (3) policies that are parallel policies. However, in reality, there might also be a hindering effect between different policies, perhaps due to the inappropriate time sequence of the policies. For example, if the measures for improving people's environmental awareness are implemented in advance of a rebate program, one of the interactions between these two policies could be that more people utilize the rebate, while another result could be that because consumers have already contributed to energy savings by altering their lifestyle as their incremental awareness increases, they are hindered from participating in the rebate program, and vice versa. In this case, the rebate policies that are supposed to increase technology efficiency will not work as expected. This behavior could also occur between social-norm-related policies and technology improvements. Sometimes such hindering effects are not easily perceived, resulting in the failure of the planned policies. Therefore, when the interdisciplinary policies are implemented together, the overall effect should not be calculated as the sum of the effects of every single policy; instead, the system that can reflect the policy interactions from the consumers' behavioral perspective is required. To date, few attempts have been made to systematically couple these insights into a quantitative framework. As a result, a serious methodological gap exists between the perceived importance of closing the loop from the energy demand side and quantitative modeling frameworks or even policy scheme analysis.

5.5.2 Case Study: A Dynamic Active Energy Demand Management System

This section outlines a trial analysis to address the methodological gap noted above by extending the analysis in Sects. 5.3 and 5.4 to a simulated dynamic active energy demand management system (DAEDMS), which evaluates the collective effects of a set of nonprice policies, including urban planning, soft policies for improving household/individual unobserved factors (such as ABC factors),

technology improvement/rebate programs, market end-use diffusion control, and social norms, on changing household behavior (i.e., end-use ownership, technology efficiency choice, and end-use usage) and the accompanying energy consumption in the residential and private transport sectors. The timing effect of each policy is also considered in DAEDMS, on the one hand to account for the interactions between the policies, and on the other hand to show the possible pathways to achieve the target. To present the implementation of DAEDMS, Beijing is taken as an example. The core model structure in DAEDMS builds on the methodology (i.e., the logit and resource allocation model) proposed in Yu et al. (2013a) and the estimation results related to self-selection effects in Yu et al. (2012). DAEDMS includes six modules, of which four modules directly act on the static policy variables (the technology improvement/rebate module, the soft policy for the ABC change module, the land-use change module, and the sociodemographic/economic factor (SDEF) change module); the other two modules play the role of introducing the dynamic change due to the market and other households (the market diffusion change module and the neighborhood social interaction module). Compared with the existing top-down and bottom-up energy system models (Fortes et al. 2014), such as decision analysis-based energy modeling (Wang and Poh 2014) and the demand side management system in the power sector (Jalali and Kazemi 2015), DAEDMS is focused on the energy demand side in both residential and private transport sectors, but with much more detailed and in-depth description of the behavioral mechanisms for household energy consumption, especially the interaction between residential energy consumption behavior and travel behavior, the rebound effects when the technology improves, the self-selection effects when the residential environment changes, the ownership change when the end-use penetration increases in the market, and the inefficient consumption and minimum service demand when considering the social influence. Furthermore, the interactions between policies within one scheme caused by the timing effect are explicitly incorporated in DAEDMS.

(1) *Referring aspects in the simulation*

In the simulated DAEDMS, the base year is 2010 and the future five years of 2011–2015 are targeted. Although the period can be easily extended, a short-term projection assuming similar economic and societal environment in the future is recommended because the adopted model estimation result is based on cross-sectional data. The following aspects in DAEDMS are addressed:

1. the natural change of the sociodemographic and socioeconomic characteristics (e.g., income, retirement with age increase, and the presence of children younger than 12 years) in the future year;
2. the influence of technology improvement or the rebate policy that causes the end-use efficiency changes;
3. the influence of soft policy (e.g., proenvironmental education);
4. the influence of the urban planning policy that changes the number of surrounding facilities;

5. the influence from the change of the market diffusion rate of the end uses;
6. the influence of social norms due to the households living in the same neighborhood;
7. the inefficiency level of the end uses and the minimum energy required for each end use.

(2) *Embedded model for predicting the future end-use consumption in DAEDMS*

DAEDMS is developed to evaluate the collective effect of the policy scheme on changing household energy consumption in the future. To that end, the logit and resource allocation model (Logit & RA) is embedded in DAEDMS to predict the end-use energy consumption every time certain policies occur. This model is derived from the combination of the model structure in Yu et al. (2013a) and model results in Yu et al. (2012). Based on the results of the mixed MNL–MDCEV model in Table 5.3, the unobserved factors associated with self-selection effects are extracted. By including these factors and household socioeconomic characteristics as well as residential environment attributes and technology efficiency collected from the household survey into the Logit & RA model and estimating it, the model coefficients used for dynamic simulation are finally obtained. In this way, we can describe how urban planning, soft policy, and technology improvement affect household energy consumption behavior in the same model structure, while dealing with both rebound effects and self-selection effects.

(3) *Interface and flowchart of DAEDMS*

A visual user interface was designed for DAEDMS (Fig. 5.5), in which the parameters for controlling policy interventions in the simulation program can be set externally based on the survey data or assumptions. The parameters shown in the interface are regarded as the policy parameters. In addition, policy makers can select the years to implement different types of policies to find the potential pathways to achieve energy conservation. If certain policies are not included in the policy scheme, then 0 is input to the corresponding option box for the policy year.

Households first access the four parallel modules (the technology improvement/rebate module, the soft policy for the ABC change module, the land-use change module, and the SDEF change module) to update their technology efficiency, unobserved factors related to ABC, residential environment, and SDEF; next, the market diffusion change module is accessed to ensure that the end-use ownership keeps pace with the whole market; finally, the social interaction module is accessed to indicate the interaction with other households. The concrete flowchart and interpretation of each module can be found in Yu et al. (2015).

In DAEDMS, we set the policy year option for technology improvement, soft policy, and urban planning policy; regarding the influence of the market and the social network, we assume that it always exists. The time step is set as one year, meaning that household energy expenditure will be re-estimated every year. However, it is easy to shorten the time step to one month or one day, and the continuous implementation of a policy (i.e., more than one year) can be easily

Dynamic Active Household Energy Demand Management System

PSO & Program Setting

Iteration

Coverage Check

Weight Min

Weight Max

Year

E Increasing Rate

Soft Policy for the AAB Change

Policy Year

Household Coverage Rate

Mean of change rate

Standard Error of change rate

Market Diffusion in year t

$Y(t)=AY(t-1)+B$

	A	B
1_Fridge	<input type="text"/>	<input type="text"/>
2_Fan	<input type="text"/>	<input type="text"/>
3_AC	<input type="text"/>	<input type="text"/>
4_Shower	<input type="text"/>	<input type="text"/>
5_Washer	<input type="text"/>	<input type="text"/>
6_TV	<input type="text"/>	<input type="text"/>
7_PC	<input type="text"/>	<input type="text"/>
8_Oven	<input type="text"/>	<input type="text"/>
9_Car	<input type="text"/>	<input type="text"/>

Technology- Improvement/Rebate

Policy Year

Household Coverage Rate

End-use Coverage number

	Mean	Standard Error
1_Fridge	<input type="text"/>	<input type="text"/>
2_Fan	<input type="text"/>	<input type="text"/>
3_AC	<input type="text"/>	<input type="text"/>
4_Shower	<input type="text"/>	<input type="text"/>
5_Washer	<input type="text"/>	<input type="text"/>
6_TV	<input type="text"/>	<input type="text"/>
7_PC	<input type="text"/>	<input type="text"/>
8_Oven	<input type="text"/>	<input type="text"/>
9_Car	<input type="text"/>	<input type="text"/>

Neighborhood Social Interaction

Mean of change rate

Standard Error of change rate

Land-Use Change

Policy Year

	Mall	Amenity	Restaurant	Park	Bus line	Train line
Neighb_1	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>
Neighb_2	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>
Neighb_3	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>
Neighb_4	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>
Neighb_5	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>
Neighb_6	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>	<input type="text"/>

Fig. 5.5 DAEDMS interface (Yu et al. 2015). *Note* The base year is 2010, the 1st policy year is 2011, the 2nd year is 2012, and the 5th year is 2015

implemented in this program. Here, we only provide an example of how to manipulate such an integrative policy analysis system for household energy consumption behavior.

(4) *Simulation results on policy effects*

Because of the lack of data, several assumptions have been made in the simulation process, which results in less reliable estimation of the policy effects. Nevertheless, the main focus of this study is to demonstrate how to evaluate quantitatively the overall effect of this policy scheme on household energy consumption behavior rather than proposing effective countermeasures for policy makers.

Regarding the outputs, the simulated DAEDMS produces the annual energy expenditure and consumption for each end use in every household in the targeted period (2011–2015 in this empirical analysis). In addition, the effects of policy schemes (or scenarios) composed of a single policy or multiple policies can be examined for any predefined execution time for the relevant policies. To evaluate the overall effect of policy schemes and to examine the timing effect, the policy scenario in the empirical analysis refers to the scheme including all of the DAEDMS policies with predefined policy years, and the scenario with only the influence of the market diffusion rate and social interaction is set as the reference scenario.

With the increasingly saturated diffusion of end uses in the market and the influence of the social network, the annual growth rate of household energy consumption decreases significantly in the reference scenario. This result suggests

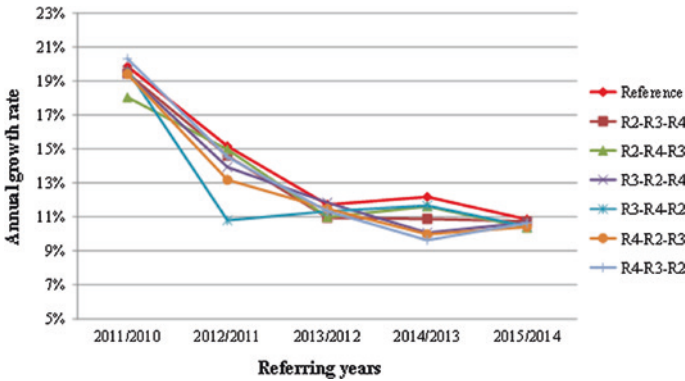


Fig. 5.6 Annual growth rates of policy scenarios. *Note* R2-S3-L4 is used to index the policy scenario, which means that the technology improvement/rebate is performed in the second year (2012), the soft policy in the third year (2013), and the land-use policy in the fourth year (2014). The same meanings are retained for the other scenarios

the effectiveness of market regulation and social interaction-oriented policies for reducing household energy use. Compared with the reference scenario, the lines of all of the policy scenarios are under the reference line (Fig. 5.6), and the predicted energy consumption at the end of 2015 will be reduced by 2–12 % (Fig. 5.7), meaning that the other three policies (i.e., rebate program, soft policy, and land-use policy) effectively achieve further energy conservation in the household sector. Nevertheless, these results reveal the variant efficacy of the same policy scheme, but with different execution timings. In other words, the interactions between policies caused by sequential implementation exist and are nonnegligible for evaluating the genuine collective effect of the policies within the same scheme.

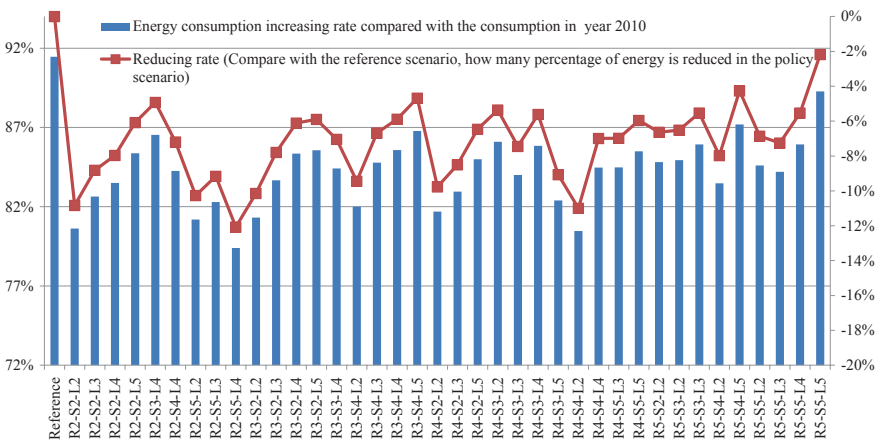


Fig. 5.7 Annual growth rates of policy scenarios

5.5.3 Summary

Section 5.5.2 provided an example of how to conduct interdisciplinary policies and evaluate their collective effectiveness. Results in the case study reveal that the policy scheme, composed of a technology improvement/rebate program, soft policy for improving household/individual unobserved factors (e.g., ABC factors), urban planning, market end-use diffusion control, and social norms, play a positive role in changing household energy consumption behavior and accordingly reducing energy use; however, the efficacy varies significantly with the execution time periods of the policies. This important finding emphasizes the need to develop a comprehensive policy management system, such as DAEDMS; at the same time, it admonishes policy makers to realize that seemingly irrelevant policies might affect each other in operation. These results imply that the current fragmented regime of policy making in different departments is undesirable.

Thus far, the integrative methodology for supporting active energy demand management is found wanting, in part due to data limitations. To continue the analysis on comprehensively capturing the influence of policy on household energy consumption behavior, the required data information is summarized as follows:

- (1) household willingness to participate in the rebate program or to purchase new efficient technologies (renew or not, buy or not) and the old end uses they want to renew (what to renew), together with their choice of the new model (which type to buy);
- (2) whether households will change to a more efficient lifestyle under the circumstance of environmental education or information campaign. If yes, what will they do?
- (3) whether households (nonowners) will buy the specific end use in the future and the reason for the purchase. If households are informed of the market diffusion rate, what will they do? If they choose to buy, which type they will choose?
- (4) if the average usage or some context for energy consumption in the same social group (e.g., residential neighborhood, company, friend network, or social peer) is given to the respondent, how will they react to it? Will their behavior change? How and how much will it change?

All of these items are related to respondents' future or are envisaged scenes; accordingly, the SP-off-RP (Stated Preference off Revealed Preference) survey, which queries respondents' decisions based on their current situation, could be an appropriate tool. The questions in the survey should also include the possible change of household sociodemographics and economic attributes.

5.6 Externality of Household Energy Consumption on Health

As reported by the World Health Organization, almost 3 billion people, mostly in low- and middle-income countries, still rely on unsustainable fuels (e.g., coal, kerosene, wood, animal dung, charcoal, and crop wastes) burned in inefficient and highly polluting stoves for cooking and heating (WHO 2013). It is estimated that in 2012 alone, more than 4.3 million children and adults died prematurely from illnesses caused by exposure to such household air pollution (e.g., black carbon (BC), nitrogen dioxide (NO₂), particulate matter (PM), benzene). These statistics indicate a strong link between household energy consumption, air pollution, and health. Indeed, the health effect is determined not just by the pollution level related to energy combustion, but also and more importantly by the time people spend breathing polluted air, i.e., exposure level. Exposure refers to the concentration of pollution in the immediate breathing environment during a specified period of time (Bruce et al. 2000). In other words, the health impact is a result of lifestyle (time allocation, activity pattern, and location decision or proximity to the emission source) and household energy consumption decided by fuel choice, end-use ownership, efficiency choice, and usage.

Many studies have measured exposure to pollutants by direct monitoring, or indirectly by combining information on pollutant concentrations in each micro-environment where people spend time with information on activity patterns. For example, in the UK, Delgado-Saborit (2012) used real-time sensors to measure personal exposure to energy combustion-related pollutants such as BC and NO₂ by concurrently mapping the activities (including commuting, cooking, home activities, other activities like relaxing and entertaining, walking, and working) and microenvironments (including home, other indoors, shops, street, travel modes, and workplace). Their results identified commuting and cooking with gas appliances as the main contributors to peak exposures of NO₂ and BC. Similarly, Steinle et al. (2015) also used contextual and time-based activity data and to assess everyday exposure of individuals to short-term PM_{2.5} concentrations (using Dylos particle counters). Zhang and Batterman (2009) investigated the changes in time allocation caused by traffic congestion and exposure to benzene and PM_{2.5} concentrations, with a specific consideration of the trade-offs between increased time in traffic and decreased time in other microenvironments (e.g., in-cabin during free-flow traffic, in-cabin during congestion, near-road, home and other indoors, workplace, and outdoors). They concluded that time allocation shifts and the dynamic approach to time activity patterns improved the estimates of exposure impacts from the recurring events. Another study that examined the health risk related to travel behavior is Cole-Hunter et al. (2012), who pointed out that bicycle commuters using on-road routes during peak traffic times share a microenvironment with high levels of motorized traffic, a major emission source of ultrafine

particles. Inhaled particle count is positively associated with proximity to motorized traffic. Despite the promotion of green travel modes worldwide, concerns about health risk should be always kept in mind; e.g., the supplementary policies that would locate bicycle lanes a safe distance away from motorized traffic should be considered together.

Because household energy consumption behavior and lifestyle contribute to both indoor and outdoor air pollution, health considerations influence the development of environmental policies aimed at reducing these adverse health impacts, such as building and construction codes that define the amount of ventilation in industrial and domestic kitchens, ventilation in commuter modes, reduction of emissions from key transport modes, and urban planning (Delgado-Saborit 2012).

5.7 Conclusion

Household energy consumption is an outcome of a series of life choices including end-use ownership, end-use efficiency, end-use usage, time use, expenditure allocation, residential location choice, employment choice, and household structure decisions. It is related to all life domains and also has externalities such as impacts on health. Life-oriented methodology that considers the potential interactions between household energy consumption and other life choices would be more appropriate for investigation of this issue. However, developing a systematic framework that includes as many life domains as possible without overcomplicating the analysis is the most challenging step. Although the methodology for dealing with self-selection effects is one alternative, a structure that can portray the direct relationship is to be preferred. A comprehensive demand management system that can cover multiple life domains is one such framework.

As emphasized in this chapter, household energy consumption is composed of basic-needs consumption and higher-order-needs consumption. Policy makers need to be aware of those policies that target both basic and higher-order needs and those that are only effective for higher-order consumption. In this way, they have a general idea of the maximum influence of the proposed policies, and can then set a reasonable and feasible target. Figure 5.8 provides a guide to how the policies work for household consumption. For technology improvement, land-use policy, and lifestyle-related policy (e.g., telecommuting and ICT promotion), they may affect household energy use from basic needs to higher-order needs, because they are likely to change people's life needs. Technology improvement is a little different from other two types of policies, because it may have no influence at all on people's lives if households simply maintain their original life without any changes. However, we should always be aware of rebound effects. Therefore, it is suggested that it is better to package technology improvement with additional policies (e.g., well-designed price/tax policies) that can contain the potential rebound effects. The self-selection phenomenon was expounded in Sect. 5.4; when implementing land-use policies, some soft policies (e.g., education, information

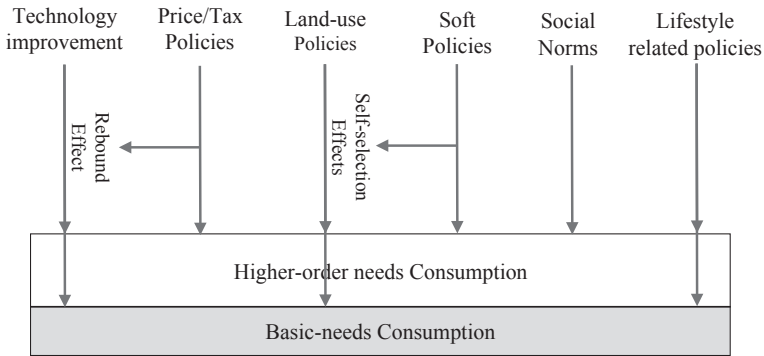


Fig. 5.8 Instructions on the policy performance

provision, and feedback) for improving household/individual ABC factors can be carried out simultaneously to diminish the negative effect and enhance the positive effect caused by self-selection. Price/tax policies, soft policies, and social norms can only have an effect on the consumption of higher-order needs. Hence, if they are likely candidates, their effectiveness should be evaluated under the constraint of minimum consumption for basic needs. In Sect. 5.5, we provided an example of the estimation of the collective effect of a group of interdisciplinary policies by considering basic-needs consumption and the applicability of a number of policies. As an initial trial, the structure is relatively simple; a more sophisticated policy assessment system, building on the viewpoints emphasized here, and a richer dataset are encouraged as the next step.

Given the apparent cause-effect relationship between lifestyle, household energy consumption, air pollution, and health, the issue concerning how a comprehensive framework should be built to unite all these domains is a challenge for the future. Existing methodologies include the residential energy demand model, the traffic model, emission inventory construction, the air quality model, the technology choice model, the lifestyle method, health impact assessment, sociological and psychological methods, all of which are relevant, suggesting that an interdisciplinary analysis is imperative.

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