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ANALYSIS

Modeling the choice to switch from fuelwood to electricity Implications for giant panda habitat conservation

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Abstract

Despite its status as a nature reserve, Wolong Nature Reserve (China) has experienced continued loss of giant panda habitat due to human activities such as fuelwood collection. Electricity, though available throughout Wolong, has not replaced fuelwood as an energy source. We used stated preference data obtained from in-person interviews to estimate a random utility model of the choice of adopting electricity for cooking and heating. Willingness to switch to electricity was explained by demographic and electricity factors (price, voltage, and outage frequency). In addition to price, non-price factors such as voltage and outage frequency significantly affect the demand. Thus, lowering electricity prices and increasing electricity quality would encourage local residents to switch from fuelwood to electricity and should be considered in the mix of policies to promote conservation of panda habitat. © 2002 Elsevier Science B.V. All rights reserved.

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1. Introduction

Dependence on fuelwood as the major energy source in rural areas of many developing countries has caused the so called "fuelwood crisis" (Dewees, 1989). For example, around half of the world's population uses biomass fuels, accounting for 35% of the energy supplies in the developing countries (World Bank, 1992). Asia, owing to its large population and the critical role that fuelwood plays in the local life, has suffered dramatically from this crisis (Food and Agriculture Organization of the United Nations, 1983). Characterized by an increasing demand for forest products, paralleled with a decreasing sustainable yield, the crisis has a range of negative consequences on the environment, including loss of biodiversity, deterioration of ecosystem services,

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soil erosion, increasing flooding, and global warming. A better understanding of the underlying mechanisms of this crisis (especially the determinants of rural household fuel substitution) is believed to be essential in relieving the crisis (Heltberg et al., 2000).

The fuelwood issue is also of significant interest in Wolong Nature Reserve (Fig. 1), one of the largest giant panda reserves in China. The giant panda (*Ailuropoda melanoleuca*), considered a national treasure of China and of concern to people around the world, has suffered from serious habitat degradation that is characterized by decreasing habitat amounts and increasing habitat fragmentation (Liu et al., 1999). In response to this situation, China's central government has established 32 nature reserves in Sichuan, Shaanxi, and Gansu provinces to protect critical habitats of giant pandas, totaling more than 16,000 km^2 (World Wildlife Fund, 2001). Commercial timber logging is prohibited in these reserves, and local residents' timber forest consumption (e.g. timber for house construction, fuelwood use) has been restricted with regard to total amount, wood species, and collection sites (Reid and Jien, 1999). Locally, special subsidies for cheaper chemical fertilizers and farming utensils are developed and provided to residents. Wolong Reserve Administration has also designated a number of areas as critical habitats and all human activities are prohibited. Furthermore, a special patrolling team has been set up to prevent poaching and illegal forest uses (Wolong Nature Reserve, 1998).

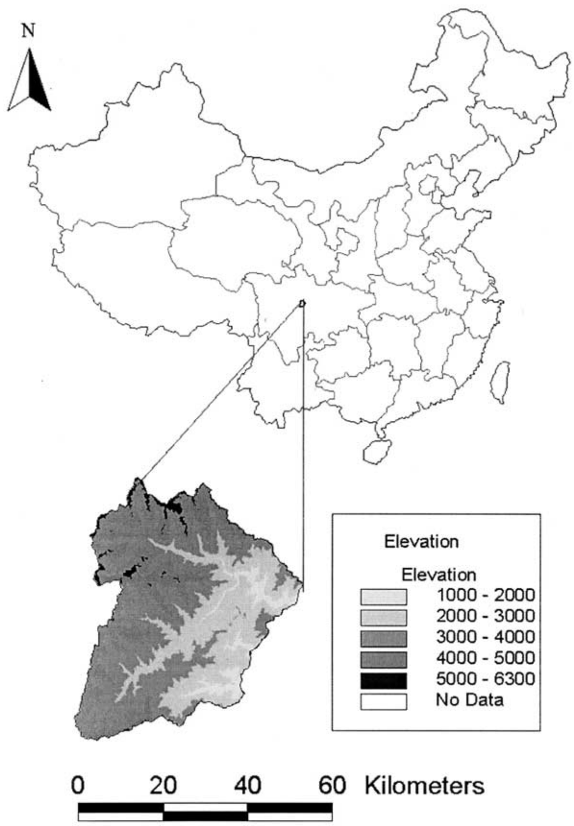

Fig. 1. The location and elevation of Wolong Nature Reserve.

Panda habitat degradation in Wolong Nature Reserve has been caused by deforestation, primarily for fuelwood collection (Liu et al., 2001a). Forests are a critical component of panda habitat, providing shelter and cover for this species. Moreover, pandas prefer to eat bamboo from forested areas—probably due to insufficient water content and decreased palatability of bamboo in areas without forest cover (Schaller et al., 1985). Recent work has shown that during the past two decades, annual fuelwood consumption has continued to increase from approximately 4000 to 10,000 m^3, while panda habitat has been reduced by more than 20,000 ha (Liu et al., 1999). The panda population in Wolong declined from 145 animals in 1974 (Schaller et al., 1985) to 72 animals in 1986 (China's Ministry of Forestry and World Wildlife Fund, 1989). The decline was at least partially due to the loss of forest cover (Liu et al., 2001a), in addition to other factors such as bamboo flowering.

Located in Sichuan (one of the most populated provinces in China), the reserve was designated in 1963 with an area of 200 km^2 and expanded to approximately 2000 km^2 in 1975. The reserve contains a rural population of 4320 people in 1998, corresponding to a total of 942 households. Households within the reserve rely mainly on growing corn, potatoes, and vegetables for subsistence, and they use fuelwood as their energy source for cooking (both human food and pig fodder) and heating in winter. Households within the reserve currently use electricity mainly for lighting and some electronic appliances, and only a small portion of them use electricity for cooking and heating.[1] Fuelwood in the reserve is not sold at the local market, and the farmers collect fuelwood mainly in winter for their own use in the following year. A recent study has found that residents in the reserve feel that in addition to the large amount of time and energy necessary for fuelwood collection, it is becoming increasingly difficult to collect fuelwood due to the shrinking forest area and the harsh topographical conditions—the elevations in the reserve range from 1200 to 6250 m, characterized by high mountains and deep valleys (Liu et al., 1999). The reserve administration has implemented many policies to restrict fuelwood collection, such as banning fuelwood collection in some key habitat areas and prohibiting some tree species from being harvested. Enforcement of these policies is difficult given the monitoring problems and the common property characteristics of the forest. Despite the restrictions and difficulties of collecting fuelwood, the majority of local households continue to use fuelwood as their main energy source, even though electricity is available throughout the reserve.

The purpose of this paper is to examine the demand for electricity for cooking and heating within the reserve. In particular, we are interested in how price and non-price characteristics of electricity combine with other factors to influence the likelihood that a household will switch from fuelwood to electricity. We use stated preference data in a random utility choice model to quantify the determinants for the choice of switching to electricity as the energy source for cooking and heating purposes. The resulting model can be used to predict how alternative energy policies (i.e. electricity price and quality) can be manipulated to reduce human disturbance of panda habitat within the reserve.

[1] A recent survey has shown that all of the households have access to electricity, although most of them only use electricity for lighting and some electronic appliances such as televisions (An et al., 2001). Crop residues and animal dung are not used as fuel because they are returned to cropland as fertilizers. Other types of energy sources such as biogas, kerosene, sun and wind power have not been used in Wolong (An et al., 2001)

Our study is significant for a number of reasons. First, panda biology and ecology have been extensively studied, but the mechanisms underlying humans' habitat-degrading activities (fuelwood collection is the key component) have not been adequately addressed, even though these aspects are crucially important for effective panda conservation (Liu et al., 1999). Our study is the first quantitative research on fuelwood substitution and electricity demand in Wolong. This research will facilitate local management of the reserve in a socially acceptable, economically feasible, and ecologically sound manner. Secondly, the framework (Section 2) and interview methods (Section 3) developed in this study would be useful for similar studies, especially those in developing countries where education, transportation, and telecommunication levels are low.

2. Conceptual framework

Lancaster's approach to consumer theory holds that utility is determined by the attributes of the goods rather than the goods per se (Lancaster, 1971). Based on this theory, the stated preference data from our household interviews will be analyzed using discrete choice methods based on a random utility model (RUM) (McFadden, 1974). The RUM is a well-established method for quantifying the preferences of individuals choosing a product (or service) from a finite set of alternatives. The simple operating assumption of the RUM is that the product chosen by a consumer yields the highest utility among all alternative products in a consumer's choice set. The model gets its name from the random terms used to characterize utility in recognition that researchers cannot measure all factors that are relevant to utility.

In our case, there are two alternatives in the choice set: (1) switch to electricity under the hypothetical situation; or (2) continue the current energy use pattern (predominantly fuelwood). Here fuelwood is the traditional and widely accepted energy source for the respondents, and they have a good understanding of the pros and cons of fuelwood consumption. For instance, they are aware that it takes time, and is getting more topographically and physically difficult to collect and transport the fuelwood, but it saves money from limited budgets by using labor which is relatively abundant. In addition, respondents using fuelwood do not have to worry about power outages that are relatively common for electricity in the reserve. Electricity, though high in price and of mixed quality, is a familiar energy source for the respondents. All the households in the reserve have access to electricity and use it for lighting and electronic appliances. As for other potential energy substitutes such as biogas and sun/wind power, we excluded them from the choice set to avoid difficulties with their unfamiliar nature—they are not currently used within the reserve and respondents were not familiar with them.

Under the choice set thus obtained, we used a vector $\boldsymbol{x}_i$ to denote electricity price, outage levels, and voltage levels. The conditional indirect utility derived from alternative 1 by individual i ($i = 1, 2, \ldots, N$), U_i^1, can be represented by the sum of an intercept α_i^1, a deterministic component $\boldsymbol{\beta x}_i^1$, and an error term ε_i^1, as follows:

$$U_i^1 = \alpha_i^1 + \boldsymbol{\beta x}_i^1 + \varepsilon_i^1. \tag{1}$$

Faced with hypothetical and current situations, if the respondent views $U_i^1 > U_i^0$ (the utility derived from alternative 0 by individual i), then individual i will adopt the first choice (switch to electricity under the hypothetical condition).

Let Y_i be the associated variable indicating individual i's choice of whether or not to switch to electricity (1 or 0), then the probability of switching is:

$$\begin{aligned}\text{Prob.}(Y_i = 1) &= \text{Prob.}(U_i^1 > U_i^0)\\ &= \text{Prob.}(\alpha_i^1 + \boldsymbol{\beta x}_i^1 + \varepsilon_i^1 > \alpha_i^0 + \boldsymbol{\beta x}_i^0 + \varepsilon_i^0)\\ &= \text{Prob.}[\boldsymbol{\beta}(\boldsymbol{x}_i^1 - \boldsymbol{x}_i^0) + \alpha_i^1 - \alpha_i^0 + \varepsilon_i^1 - \varepsilon_i^0 > 0],\end{aligned} \tag{2}$$

where U_i^1 and U_i^0 represent the utilities that are associated with choices 'switch to electricity under the hypothetical condition' and 'continuation of current energy use pattern', respectively. Vectors $\boldsymbol{x}_i^1$ and $\boldsymbol{x}_i^0$ represent the hypothetical and current electricity conditions (price, outage, and voltage levels), respectively. The terms α_i^1 and α_i^0 represent intercepts under these hypothetical and current conditions, $\boldsymbol{\beta}$ is the parameter vector associated with $\boldsymbol{x}_i^1$ and $\boldsymbol{x}_i^0$. In addition, we seek to examine the extent to which other non-electricity factors, such as demographic variables, prices of possible substitutes to electricity, and geographic locations, can also explain inter-household differences in the switch to electricity, so these types of factors (described by the vector $\boldsymbol{z}_i$ with an associated parameter vector $\boldsymbol{\chi}$) were also included. The common assumption that the error terms are distributed following a type I extreme value yields the familiar logit model (McFadden, 1974). In our case, the probabilities take the following form,

$$\begin{aligned}\text{Prob.}(Y_i = 1|\boldsymbol{x}_i, \boldsymbol{z}_i, \alpha, \boldsymbol{\beta}, \boldsymbol{\chi}) &= \exp[\alpha + \boldsymbol{\beta}(\boldsymbol{x}_i^1 - \boldsymbol{x}_i^0) + \boldsymbol{\chi z}_i]/[1 + \exp(\alpha + \boldsymbol{\beta}(\boldsymbol{x}_i^1 - \boldsymbol{x}_i^0) + \boldsymbol{\chi z}_i)]\\ &= 1/[1 + \exp(-\alpha - \boldsymbol{\beta}(\boldsymbol{x}_i^1 - \boldsymbol{x}_i^0) - \boldsymbol{\chi z}_i)].\end{aligned} \tag{3}$$

Note from Eq. (3) that the final variables entering the logit model take the form of differences in variable levels except for the non-electricity factors $\boldsymbol{z}_i$.

3. Household interviews

Our goal in this study was to estimate the demand for electricity under different conditions for electricity prices and quality, as well as relate the demand to demographic conditions. In our case, adequate market data spanning these conditions are unavailable. For instance, the amount of electricity used by each household is not accurately recorded or not available in some areas, and the variation of electricity price is small. Stated preference techniques, sometimes referred to as contingent behavior, were used to overcome this problem. It is well reported that with these techniques researchers can design surveys to elicit preferences for goods with attributes that are not currently available in markets (Rubey and Lupi, 1997). Debates on survey approaches, nevertheless, have continued for a long time—for example, the National Oceanographic and Atmospheric Administration (NOAA) panel has recommended face-to-face or telephone interviews for reliably eliciting stated preferences (Arrow et al., 1993). However, Dillman (1996), Ethier et al. (2000) argued that the shortcomings of personal interviews are generally understated, while the problems of mail surveys are overstated. Of all these potential survey approaches, we chose face-to-face interviews because the low education levels of the respondents (only 4.2 years/person, Table 1) may limit their understanding of the questions if otherwise implemented. Another consideration for the survey mode was that most of the households do not have telephones. Moreover, because the reserve is a large rural area with a topographically difficult terrain, there are large postal delivery lags that render the local postal service unsatisfactory.

In the qualitative research stage of the project, preliminary interviews were conducted with 20 households in the summer of 1999. These interviews were designed to explore possible determinants of the switch to electricity; to test people's ability to make the choices; and to collect data to help us establish the levels for the attributes. We found that most of the local households indicated they could not afford electricity for cooking pig fodder and for heating because of the high amount of energy needed for these uses. In contrast, using electricity for lighting and appliances has a much smaller effect on the household budget and there is no readily available substitute for this energy. In addition, many households indicated that the electricity quality was not satisfactory for heating and cooking purposes, primarily characterized by low voltage and frequent outages during some seasons (especially in winter due to less water available for the hydropower stations) and in some areas (e.g. some villages in Wolong Township).

Table 1
Socioeconomic and demographic profiles of the respondents

Variable	*N*	Average	Standard deviation
Age (years)	192	42.54	12.68
Education (schooling years)	192	4.12	3.49
Expense (Yuan/household/year)	192	10802.97	11822.52
Perceived price (Yuan)	192	0.13	0.10
Perceived outage levels[a]	192	1.61	0.76
Perceived voltage levels[a]	192	2.52	0.63

[a] 1 for low, 2 for moderate, and 3 for high for both perceived outage levels and perceived voltage levels (1 US \$ = 8.3 Yuan in 1999).

Based on the information obtained from the preliminary interviews we finalized the design of the questionnaires and set up the discrete levels for the three continuous variables (price, outage, and voltage). The following seven levels were chosen for the electricity prices: 0, 0.02, 0.03, 0.04, 0.08, 0.16, and 0.25 Yuan/kWh.[2] The determination of these seven levels was based on the price information from the preliminary interviews—most of the respondents chose prices from 0.02 to 0.05 Yuan/kWh as thresholds for the switch, and some chose 0 as the prerequisite for the switch. We also included three higher prices with larger increments, 0.08, 0.16, and 0.25 Yuan/kWh, to test the willingness to switch under a broad range of prices. Seven levels, which are a relatively large number of levels when compared to many choice experiments in the literature, were chosen to provide a sufficient number of data points to test for any non-linear price effects. Electricity outage frequency was set at three levels (high, moderate, and seldom corresponding to five or more times per month, 2–4 times per month, and less than two times per month). Electricity voltage was also set at three levels (high, moderate, and low, corresponding to 200 or more volts, 150–200 V, and less than 150 V). Three sets of cards (two inches wide and three inches long for each) were prepared to show the electricity information to the respondent as follows: one set (seven cards) for the seven prices, one set (three cards) for the three outage levels, and one set (three cards) for the three voltage levels.

Our sampling frame was the 1996 Chinese statewide agricultural census list, which lists all households by villages. A village is a cluster of households that live geographically close to each other (there are six villages in the reserve). Our

[2] Yuan is a currency unit in China. \$1 US = 8.3 Yuan in 1999.

sample size was set at 220 (about 23% of the total number of households). The sample size reflects the tradeoff between our need for a robust sample and the limitations from our time, budget, and manpower. We used stratified sampling by proportionally drawing the 220 households from each of the six villages based on its size (N_i, $i = 1, 2, \ldots, 6$). Specifically, within village i, we coded all the households with numbers from 1 to N_i, and then randomly sampled n_i (the sample size in village i) households from a total of N_i households in village i.

To collect the stated preference data, we interviewed the head of each household in the summer of 1999 and recorded his/her age, gender, and education. Next, we collected household socioeconomic data, e.g. household expense items in 1999 (then we summed over all the items for the annual total household expenses), educational levels, ages, genders of all household members, and so on. Respondents were then asked their current price, voltage level and outage frequency for electricity. In the section on electricity choice, the three sets of cards were placed face down in random order. We asked the respondent to pick up one card from the seven price cards; one card from the three electricity outage frequency cards, and lastly, one card from the three electricity voltage cards.[3] The question we asked (in Chinese) was: "under this condition, will you switch from fuelwood to electricity completely (for cooking, cooking pig fodder, and heating)?"

We had a 100% response rate in these interview sessions—this rate should not be surprising in Chinese rural cultures, where people like to be visited. Out of these 220 households, 28 households had problems in answering some of the questions—for example, they could not remember their current electricity price. Table 1 contains the demographic and socioeconomic profiles of the remaining 192 households available for the model estimation. The actual prices that local residents paid differed regionally because the hydropower stations within the reserve are run by different entities (companies, villages, or township governments) with different management goals, technical support teams, and production costs. These differences likely contribute to the high standard deviation of the perceived prices.

4. Model specification and estimation

The data on the households' responses to the question of whether they would switch to electricity were used to estimate a binary logit model (see Eq. (3)). The variables used to explain the choices are a combination of electricity factors, locational factors, fuelwood transportation distance factors, and demographic factors. The variables used in the model are reported in column 1 of Table 2.[4] Corresponding to the $\boldsymbol{x}_i$'s in Eqs. (1)–(3), there are three electricity-related variables in the model: price, outage frequency, and voltage (variables 5–10 in Table 2). Because the outage frequency and voltage variables take three discrete levels, each was recoded into two separate dummy variables for the respective low/seldom and moderate

[3] The experimental design was thus determined by randomly combining the three electricity attributes. This approach is somewhat distinct from the main-effects designs that are common in choice experiments. The randomized design was chosen for both pragmatic and theoretical reasons. While main-effects design plans are parsimonious and relatively efficient designs for linear models, main-effects plans preclude the estimation of interactions between variables and effects we were interested in testing for. On a practical level, the randomized design used here was straightforward and easy to implement in the field.

[4] We also evaluated two alternative models prior to our final model. The first includes only the demographic factors and provides evidence on the importance and validity of the electricity price and quality variables in explaining the stated choices. This limited model does a poor job in terms of overall model fit ($\log L = -128.41$) or parameter significance (only two factors are significant at the 10% level). A second model with only the electricity factors (price, voltage, outages) improves on the first model in terms of both overall fit ($\log L = -90.68$) and parameter significance (all are significant at 10% level, some at 5 and 1% levels). However, based on likelihood ratio tests, the model in Table 2 with the full set of variables is a significant improvement over both of the more limited models.

Table 2
Results of the logit choice model

Variable	Code	Explanation	Parameter estimate	Standard errors
Intercept			−2.3853**	(1.0588)
Age	1	Age of the respondent	0.0215	(0.017)
Gender	2	Gender of the respondent	−0.1727	(0.4476)
Education	3	Schooling years of the respondent	0.0552	(0.0666)
Expense	4	Annual household expense	0.0533**	(0.0225)
Prc_dif	5	P_1-P_0	−28.1183***	(5.0239)
Squ_dif	6	$P_1^2-P_0^2$	23.1005***	(6.9912)
V_L_dif	7	$V\_L_1-V\_L_0$	−1.1863***	(0.4007)
V_M_dif	8	$V\_M_1-V\_M_0$	0.3999	(0.3415)
C_S_dif	9	$C\_S_1-C\_S_0$	1.3418***	(0.4095)
C_M_dif	10	$C\_M_1-C\_M_0$	0.9719***	(0.3696)
Trans_L	11	Low distance (1) and otherwise (0)	−1.2417*	(0.8613)
Trans_M	12	Moderate distance (1) and otherwise (0)	−0.3363	(0.5498)
Location	13	Gengda (1) and Wolong (0)	0.6129	(0.5741)
Log *L*		Overall model fit statistics	−83.509	

The signs *, **, and *** represent significant at 10, 5, and 1% level, respectively. The numbers in brackets are the standard errors. The subscripts 1 and 0 represent the hypothetical and current conditions, respectively.

levels.[5] As indicated by Eq. (3), for each of the electricity variables, the differences in the attribute levels shown on the cards and the perceived current values of each attribute are entered as the variables in the binary logit model. In addition to the difference between the hypothetical price and the current price (P_1-P_0), the difference of the squared hypothetical price and squared current price ($P_1^2-P_0^2$) enters as a variable to capture any non-linear effects of price changes.[6]

Several non-electricity variables were used in the analysis (items 1–4 and 11–13 in Table 2), corresponding to the z_i in Eq. (3). Demographic variables include the respondents' age, gender, education (total years of schooling for the respondent), and household annual expenses. We chose household annual expenses as a proxy for annual income, in part due to the difficulties in collecting reliable information from the respondents about their incomes. The household expenses will roughly track incomes, although for our sample about 20% of the expenses go toward income producing activities such as farming. Thus, to some extent, the expenses variable reflects differences in incomes as well as potentially reflecting differences in the size of farming operations. The transportation distance variables, reflecting the distance between fuelwood collection sites and major roads, are included because they are proxies for the costs associated with fuelwood collection. The geographic location variable indicates which of the two townships within the reserve that the household resides in (*Location*, 1 for Gengda Township and 0 for Wolong Township). Of the two townships that constitute the reserve, Gengda

[5] The voltage level was expressed with two dummy variables, low voltage (V_L, 1 for low and 0 for otherwise) and moderate voltage (V_M, 1 for moderate and 0 for otherwise). Similarly, outage frequency was expressed by two dummy variables: seldom cutoff (C_S, 1 for seldom and 0 for otherwise) and moderate cutoff (C_M, 1 for moderate and 0 for otherwise). Two dummy variables were used to express the transportation distance factor: moderate distance (*Trans_M*, 1 for moderate and 0 for otherwise) and short distance (*Trans_L*, 1 for short and 0 for otherwise).

[6] Unlike the more common main-effects designs for choice models, our randomized design allowed us to test for interaction terms. To evaluate the effects of the interactions between the above variables, we tried the following terms: (1) hypothetical price (P_1) vs. voltage (V_L or V_M); (2) hypothetical price (P_1) vs. outage (C_S or C_M); (3) outage vs. voltage (e.g. C_M*V_L); and (4) price difference (P_1-P_0) vs. outage difference ($C\_M_1-C\_M_0$). The regression results show that these interactions improved the model fit very little. For instance, the model with $(P_1-P_0)*(C\_S_1-C\_S_0)$ only increased the log L from −83.509 (Table 2) to −82.003. For model parsimony, we did not include these terms in the final model.

Township has less forest cover than Wolong Township, making it more difficult to collect fuelwood. Residents of Gengda also appear to be more likely to work or sell goods outside the reserve, which might raise the opportunity cost of time available for collecting fuelwood. The constant term represents females, high voltage, high outage frequency, high transportation distance, living in Wolong Township, and any other factors associated with alternative 1 (where 1 is the 'switch to electricity for cooking and heating').

Table 2 reports the parameter estimates, standard errors, significance levels, and the log likelihood value for our model. The performance of our model was further examined by using the empirical data on household's willingness to switch to electricity at different price levels. At price levels of 0, 0.02, 0.03, 0.04, 0.08, 0.16 and 0.25, the proportions of households that agreed to switch were 0.61, 0.86, 0.56, 0.59, 0.44, 0.18, and 0. The predicted probabilities of switching at these price levels were 0.80, 0.70, 0.65, 0.59, 0.37, 0.12, and 0.04, respectively.[7] The predicted probabilities at each price level are the average of the predicted values for the portion of the sample receiving that price level. A paired t-test was preformed on the predicted and observed proportions resulting in $t = -0.10$, $P = 0.925$, with d.f. $= 6$. This simple test implies that the null hypothesis (the difference between model predictions and the observed data is zero) cannot be rejected at the 5% level of significance.

[7] Note that these empirical frequencies are the averages across the choices for individuals receiving the respective prices and therefore include individuals who received various levels of the outage and voltage variables. For example, almost all of the individuals who were willing to switch at the prices (0.16 and 0.25 Yuan) that are higher than the current average of 0.13 Yuan drew cards with the high voltage level, the low cutoff frequency or both. Thus, improved quality influenced the choice. In addition, models without the squared term on prices tended to substantially overestimate the probability of switching at higher prices when compared to the empirical proportions.

5. Results and discussions

As expected, price has a significant and negative effect on households' willingness to switch to electricity for cooking and heating (see Table 2). In addition, the squared term for the prices is significant and positive. Taken together, the results show that the choice probability decreases as price rises, and the rate of decrease falls as price rises.[8] Thus, the results indicate that demand is more price-sensitive at low prices than at higher prices than would be the case with just the linear effect. Also evident from Table 2 is the importance of the non-price electricity factors. Low voltage levels significantly reduce households' willingness to switch to electricity relative to moderate and high voltage levels. The moderate voltage level did not have a significant effect on choices. Lower outage frequencies (i.e. cutoff seldom, C_S, and cutoff moderate, C_M) significantly increase households' willingness to switch to electricity relative to high outage frequencies, with the seldom level having a larger effect than the moderate level. Taken together, the electricity price and quality variables provide clear and intuitive signals about households' energy decisions.

The signs of the other parameters in our model (Table 2) are consistent with our insights into the local situations. For instance, the annual expenditure, a proxy for household annual income and perhaps farm size, has a positive sign, indicating that higher income households are more likely to switch to electricity than those with less income. As expected, the sign for the low transportation indicates that the shorter the fuelwood transportation distance, the less likely the household is to switch to electricity, though this effect is only significant at the 10% level. The location factor has a positive sign, meaning the people in Gengda Township (coded as 1) are more likely to switch

[8] The empirical curvature implies that at some prices the choice probability would no longer be decreasing in prices. However, this would not occur until price reached about 10 times the current price, which is well outside the relevant range of the data.

than those in Wolong Township (coded as 0) but the effect is not significant in our model. It was anticipated that this variable would have an impact for the following reasons: (1) there is less forest in Gengda, so the time and labor needed to collect fuelwood are higher; (2) the households in Gengda spend more time on commercial activities outside the reserve (e.g. transporting the local cabbage to surrounding cities such as Chengdu, the capital city of Sichuan province) and have a potentially higher opportunity cost of time.

Several implications of the results emerge. First, households' willingness to switch to electricity is clearly dependent on the cost. However, the results also reveal the important role that non-price characteristics of electricity might inadvertently play as barriers to electricity adoption. Thus, both electricity price and quality are relevant considerations in any energy policies aimed at conservation of giant panda habitat. Second, the results on the expenses variable suggest that investment in increasing income (e.g. through providing job opportunities) of households within the reserve will likely reduce dependence on fuelwood. Third, the underlying data on current conditions reveal that the electricity quality in Gengda Township was better than in Wolong Township. The voltage and outage differences in Wolong and Gengda Townships suggest the potential for targeting approaches to improving electricity demand in differing parts of the reserve, e.g. more effort may need to be paid to increase voltage and lower the outage frequency in Wolong Township.

Fig. 2 presents an illustration of the estimated demand curves under baseline conditions as well as under alternative assumptions on voltage levels and outage frequencies. For clearer illustration, we only present three curves corresponding to baseline, low voltage, and outage scenarios. The curve for high outage is very close to that for low voltage, and the curves for normal voltage and moderate outage are very close to that for the baseline. The demand curves in Fig. 2 were computed using the parameters specified in Table 2. For each of the curves, the switch probabilities were computed over the range of prices and were averaged across the 192 households. For each curve, the demographic and geographic variables were held at their initial levels. For the 'baseline' curve, we computed the probabilities by holding constant the current electricity price (P_0) and varying P_1 (hypothetical price). For the 'baseline' curve, the voltage and outage frequencies are held at their current values. The other curves in Fig. 2 were computed similarly except that the voltage and outage frequencies in the hypothetical conditions were set at the indicated level. For example, the curve "Voltage Low" in Fig. 2 was computed with the new voltage level set so that '$V\_L_1 = 1$' for all households.

Inspection of Fig. 2 sheds light on the current situation for electricity demand and quality. The baseline demand curve is close to the curves that correspond to normal voltage and moderate outage, but higher than the two curves for low voltage and high outage—this implies that currently, the electricity voltage is not too bad, but the households in the reserve suffer from a moderate outage level—this is consistent with the survey data in Table 1. Another point that should be made is that the shift of the probability curves (or demand curves) in Fig. 2 reflects people's responses towards electricity quality. When voltage is low or outage frequency is high, the associated demands (represented by the two curves for low voltage and high outage in Fig. 2) are pulled down quite a lot, especially at the low price levels. When voltage is normal or the outage frequency is low, the demands have a comparatively larger increase, especially at low price levels. Again, a management implication is that one way to encourage more people to use electricity is to improve quality. Some quantitative figures may be more useful for local managers. For example, at price of 0.13 Yuan/kWh, the model predicts that an improvement in outage (from current frequency to the "seldom" level) will result in 6% more households switching to electricity (from 18 to 24%). However, if the outage frequency increases, around 8% of the households (around half of the current electricity users) will revert to dependence on fuelwood. If electricity quality (voltage and outage) remains unchanged in the baseline curve, a decrease in price from 0.13 to 0.10 will lead to about 10% more households switching to electricity.

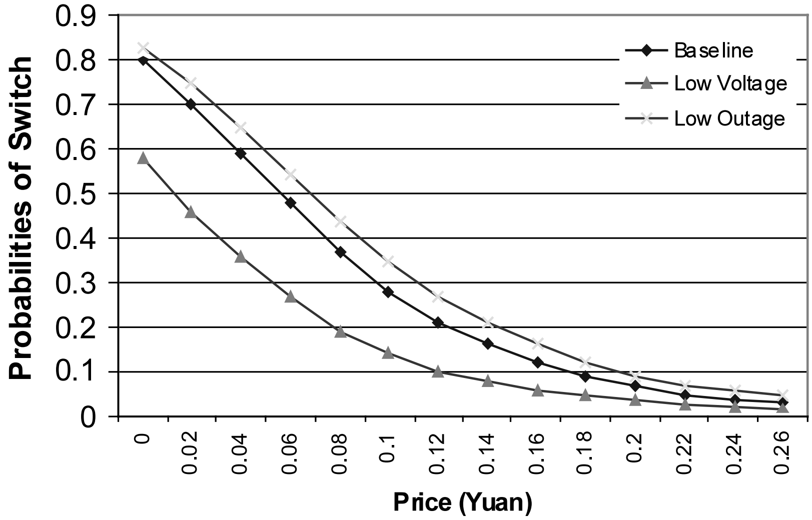

Fig. 2. Probabilities of switch under different combinations of price, voltage, and outage levels. The curve for high outage is very close to that for low voltage, and the curves for normal voltage and moderate outage are very close to those for the baseline. For clearer illustration, they are not displayed.

To further illuminate the willingness to switch to electricity for cooking and heating, we computed price elasticity at the average price of 0.13 Yuan/kWh by using Eq. (4):

$$\text{Elasticity} = \frac{\partial \pi}{\partial P_1} \times \frac{P_1}{\pi} = (1-\pi)(\boldsymbol{\beta}_1 P_1 + 2\boldsymbol{\beta}_2 P_1^2), \quad (4)$$

where π is the probability of switching under the condition of interest, P_1 is the hypothetical price (0.13 here), $\boldsymbol{\beta}_1$ (−28.1183) and $\boldsymbol{\beta}_2$ (23.1005) are coefficients for $(P_1 - P_0)$ and $(P_1^2 - P_0^2)$ in our model, respectively (Table 2). Under the conditions corresponding to baseline, low voltage, normal voltage, low outage, moderate outage, and high outage levels, the elasticity values at the price of 0.13 are −1.67, −2.22, −2.00, −1.30, −1.58, and −2.00, averaging −1.80. This average elasticity of −1.8 means a 1% increase in price would lead to 1.8% decrease in electricity demand, or equivalently, 1.8% increase in fuelwood demand because no other energy sources could act as a substitute for electricity. Thus, the demand for electricity for heating and cooking in Wolong Nature Reserve is price elastic.

The price elasticity results and the price–demand relationship shown in Fig. 2 have significant management implications. Because demand is so sensitive to price, any price change should be made with full consideration of the possible consequences. For instance, there was a rise in electricity price (an increase around 0.05 Yuan/kWh) in Gengda Township in 1999; as a result, many farmers who had abandoned fuelwood consumption started to collect and use fuelwood again (Yang 1999, personal communication). Consequently, panda habitats must have been degraded to some extent.

Given the estimated model, we can predict the percentage of households switching to electricity under different electricity improvement regimes. These results can be translated into an estimate of the reduction in fuelwood collection. The average annual amount of fuelwood consumed by a household is 17.03 m^3/household per year (An et al., 2001). With this information, we could compute the amount of fuelwood that could be saved in the whole Wolong Nature Reserve through these quality improvement regimes by using Eq. (5):

$$\text{Amount} = \bar{\pi} \times \bar{s} \times N, \quad (5)$$

where $\bar{\pi}$, $\bar{s}$, and N are average probability change under an electricity improvement regime (price, outage, or voltage change), the average annual amount of fuelwood consumed by a household, and total number of households in the reserve, respectively. Given $N = 942$, $\bar{\pi} = 6\%$, and $\bar{s} = 17.03$, a rough estimate of the total amount of fuelwood that could be saved per year just from a permanent outage improvement would be computed as $942\% \times 0.06\% \times 17.03 = 962.54$ m^3. Given the amount of fuelwood saved through improved electricity quality or decreased price, reserve managers can analyze the impacts on the quantity and quality of panda habitat.

6. Conclusions and future directions

Energy policies that stimulate electricity use in Wolong Nature Reserve will reduce dependence on fuelwood and will help protect dwindling giant panda habitat—critical habitat that is threatened by human disturbance despite its location within a nature reserve. Our model has helped explain why many people living in the Wolong Nature Reserve have not switched to electricity under the current conditions. The model provides insights into the quantitative interactions between electricity demand and different demographic and electricity management factors. The results indicate that the probability of switching to electricity was price elastic. Importantly, the results also show that electricity quality (outage frequency and voltage) have significant effects on adoption. For example, at the current average price of 0.13 Yuan/kWh, a 0.05 Yuan decrease in electricity rates would double the predicted number of households using electricity for cooking and heating. However, if this price decrease were accompanied by a shift to the high outage frequency, then we would not predict any change in households using electricity. Thus, the combined effect that any proposed energy policies would have on both electricity price and quality should be considered when evaluating the potential effect on fuelwood use and panda habitat.[9]

[9] Since immigration into the reserve is prohibited except through marriage, subsidizing electricity price and quality will not inadvertently induce households from outside the reserve to settle within the reserve.

To lower electricity price and increase the quality, the reserve administration will need to find financial support from various sources, such as central or provincial governments, and developing/managing local eco-tourism (already existent on small scale). Recently, a ‘eco-hydropower plant’ is under construction, and it is anticipated that upon completion this facility will provide cheaper and more reliable electricity to many local residents (An, 2001, personal field observation). In addition, the reserve administration and Luneng Group have contracted for an eco-tourism program with an expected investment over 0.2 billion Yuan, and part of the revenue from this program would be used to subsidize electricity costs for local farmers (Mingcong Liu, 2001, personal communication). These initial steps have shown that our suggestions are feasible and of interest to reserve managers.

There are several aspects of fuelwood use that may warrant further inquiry. First, some cultural or traditional perceptions may help to further explain the switch from fuelwood to electricity. For example, some individuals may prefer to use fuelwood due to the tradition of using fuelwood, or because he/she feels most comfortable/safe by using fuelwood, and so on. A better understanding of these other non-price factors would likely further improve the model. Such factors might also illuminate opportunities for panda conservation (e.g. education programs or electricity demonstration projects). Secondly, if we were able to increase our sample size, some of the existing non-electricity factors might have more explanatory power (e.g. the age and education factors). Nonetheless, the model performed well even with the current sample size.

It may be that some households would only partially switch to electricity as their household characteristics change or as the electricity factors change. Similarly, some households might switch for some, but not all, energy uses (e.g. they may switch for heating and cooking human food, but not for cooking pig fodder). In contrast, we asked people whether they would completely switch to electricity for all cooking and heating uses under the hypothetical conditions. Based on our preliminary research and difficulties with this type of question in other settings, we did not attempt to collect stated preference data on the ‘quantity’ dimension of the electricity choice. However, the success of the current research and the ability of the respondents to handle the discrete choice task suggest that it might be possible to ask respondents about partial shifts to electricity or to further distinguish among electricity uses. For example, the question might be posed in terms of the fraction of cooking and heating (e.g. 0, 1/4, 1/2, 3/4, 1) that would be done with electricity under different conditions rather than phrasing the question to directly elicit quantity in terms of kilowatt hours of electricity. Future research could be directed at determining whether such a stated preference format would also be successful.

The present study provides information on the potential effectiveness of electricity subsidies for protecting panda habitat. However, this information is only part of what is needed to estimate the cost function for protecting panda habitat. Future efforts may seek to obtain data on the costs of different measures for reducing fuelwood collection (such as subsidizing electricity), along with ecological data on the associated impacts on panda habitat/populations, in order to predict the changes in panda habitat (in terms of amount and distribution) and population size given various monetary investments.

Of course, other alternatives may be complementary to our proposed measures. First, local residents’ fuelwood stoves might be reformed to use fuelwood more efficiently. In the late 1980s, the reserve administration subsidized a stove-reformation program which proved unsuccessful because most farmers felt these stoves were inconvenient and hard to use in winter for cooking pig fodder (Zhou, 1999, personal communication). Rather than solely considering energy-use efficiency, the stove-reformation program, if initiated in the future, needs to take into account easiness to use and capability to cook large amount of pig fodder in winter. Second, an education campaign that increases the awareness of the local residents of the increasing scarcity of forests and the importance of panda conservation might also reduce fuelwood use. The failure of the aforementioned stove-reformation program was partially due to the ‘common property tragedy’—if forests are viewed as unlimited and thus free, why do local residents bother to reform their stoves? Third, planting fuelwood-oriented trees in non-habitat areas might help to relieve the conflicting needs of forests between people and pandas. The reported success of a recently initiated statewide program called ‘Grain-to-Green’ may provide evidence for this measure (Xu, 2002). This program provides local farmers with free rice, wheat flour, tree seedlings, and a certain amount of cash given that they return a designated portion of their croplands and plant designated trees instead. Lastly, a more efficient and effective approach in the long run may be to invest on education of local farmers’ children, encourage them go to colleges/technical schools, and find jobs/settle in cities (Liu et al., 2001b). Previous efforts to subsidize the relocation of local farmers have failed because many farmers returned to Wolong after living outside the reserve for some time. The local farmers, though unwilling to relocate themselves due to many reasons such as lack of land and inability to adapt to outside climate or culture, do hope their children have opportunities for higher education and jobs outside the reserve (Liu et al., 2001b). This is more effective insofar as relocated young people will have their offspring (children, grandchildren, and so on) outside the reserve. These experiences and our results indicate that subsidizing electricity prices and improving electricity quality, in combination with other approaches mentioned above, would benefit local residents while conserving giant pandas.

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