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Household fuel choice in urban China: A random effect generalized probit analysis*

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Abstract

Using seven rounds of household survey data that span more than a decade, this paper analyzes the determinants of household fuel choice in urban China. Unlike the existing studies, we use an empirical strategy that takes into account the potential heterogeneous effects of socio-economic factors in households' preference ordering. Robustness of this empirical strategy is checked against alternative methods. The results show that household fuel choice in urban China is related to fuel prices, household's economic status and size, and household head's gender, education and occupation. Our results suggest that policies and interventions that raise household income, reduce prices of clean fuel sources, and empower women in the household are of great significance in encouraging the adoption of clean energy sources.

JEL classification: C25, Q23, Q40, Q42

Key words: Household fuel choice; Panel data; Random effect generalized probit model; Urban China

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1.Introduction

Half of the world's population and up to 95 percent of people in developing countries rely on solid fuels (biomass fuels and coal) to meet their energy needs (IEA, 2011). Household dependence on solid fuels for cooking has health and environmental impacts. Conservative estimates document that exposure to indoor smoke produced by household solid fuel combustion is responsible for about 2 million premature deaths per year globally, which is 3.3% of the global burden of disease. About 548,900 of these deaths occurred in China alone in 2004 (Smith et al, 2004; WHO, 2008).

With increasing household well-being and income in China, especially in the urban areas, more and more households have shifted from the traditional firewood or coal to modern energy, such as liquefied natural gas (LNG) or electricity. China's experience makes it a good example to investigate the economic and social determinants of household cooking fuel choices. Understanding these determinants will be helpful in finding ways to accelerate the transition to cleaner fuels in developing countries generally.

Traditionally, the 'energy ladder' hypothesis has been used to explain households' fuel choices and switching strategies in developing countries. This hypothesis describes income as the sole factor in determining these decisions. However, fuel choice behavior of households is not as simple as prescribed by the traditional energy ladder hypothesis (Masera et al. 2000;

Heltberg 2005) and the simple association between income and fuel demand (choice) has been criticized in recent literature because fuel choice can be affected by multitude of demographic and socio-economic factors (Masera et al. 2000; Heltberg 2005; Mekonnen and Köhlin 2008).

A number of previous studies analyzed the determinants of household's fuel choice in the developing world. However, many of these studies are based on cross-sectional data (e.g., Hosier and Dowd, 1987; Leach, 1992; Farsi el al., 2007) and studies employing panel data are rare (e.g., Mekonnen and Köhlin 2008). Moreover, previous studies in China are mainly based on aggregate statistics or on surveys conducted in certain province or counties (e.g., Chen et al., 2006; Wang and Feng, 1997; ESMAP, 1996). As far as we are aware, very few studies have examined household energy choices in China through longitudinal data from a nationwide household survey. This paper tries to fill this gap by using seven-round panel data from the China Health and Nutrition Survey (CHNS). This panel data enables us to control for unobserved individual heterogeneity and time trends in the analysis of household fuel choice.

This study focuses on households' primary cooking fuel choices in urban areas of China only due to the fact that the fuel choices of rural households are largely determined by fuel availability and opportunity costs for fuel collection rather than by budget constraints, which complicates the modeling of household fuel choice in such circumstances (Farsi el al., 2007). Further, while fuel choices on cooking and heating are the main interests of the literature on household energy choices, this paper concentrates on households' cooking fuel choice given the fact that heating in urban China is mainly provided at the district level, which means that households have little freedom to choose the type of heating energy used. Finally, we focus on households' choices of primary cooking energy. Primary cooking energy is the type that is most frequently used by a household.[1] Farsi el al. (2007) used a similar definition in their study of fuel choice in India.

In line with Farsi el al. (2007), ordered probit models were employed to take into account the potential ordering of different fuels in terms of efficiency or convenience. In addition, we contribute two extensions to the application of an ordered discrete choice model to the fuel choice issue. First, one of the limitations of the standard ordered probit model is the parallel regression (or constant odds ratio) assumption implied in it. That is, coefficients that describe the relationship between, say, the highest category and all lower categories are the same as those that describe the relationship between the lowest category and all higher categories. This assumption may not hold in the context of household fuel choice. For example, the economic cost (effort) required to change from firewood to coal may not be the same as that for changing from coal to natural gas. Therefore, the generalized ordered probit framework, rather than the standard ordered probit model, was employed to account for the potential heterogeneous effects of explanatory variables across different fuels. Second, to explore the

[1]The survey identifies the cooking fuel used most frequently by a household. Due to lack of information on the proportion of each fuel for the households that use multiple fuels, it is difficult to effectively incorporate the multiple fuel choices into our estimation.

panel structure of the data set, the generalized ordered probit model with random effect specification was adopted to analyze the household choices.

Our results suggest that policies and interventions that raise households' income, reduce prices of clean fuel sources, and empower women in the household are of great significance in encouraging the adoption of clean energy sources. The results also show the importance of other socio-demographic factors, such as education and occupation of the heads in determining the choices of primary cooking fuels in urban Chinese households.

This paper is organized as follows. Section 2 provides a brief review of related literature. Section 3 describes the empirical strategy used in this study. Section 4 presents the data and some descriptive statistics. The estimation results of our econometric model are illustrated and discussed in Section 5. Finally Section 6 summarizes the conclusions and policy implications.

2. **Review of Literature**

A growing body of empirical studies tries to investigate energy choices and switching strategies of households in developing countries. These studies focus on the effect of household characteristics, income and prices on fuel choices and also on the validity of the 'energy ladder' hypothesis. In the paragraphs below, we present a brief review of previous studies, focusing on households' fuel choices and switching strategies, and highlighting existing knowledge gaps.

The ‘energy ladder’ hypothesis is based on the assumption that households are exposed to a number of fuel choices, which can be ranked in order of increasing efficiency and technological sophistication, and that households make the transition to the higher-ranked fuel as their income rises (Hosier and Dowd, 1987). Electricity, natural gas and other commercial fossil fuels are ranked higher than the traditional biomass fuels. The energy choice of a household will move ‘up’ the energy ladder to higher-ranked fuels as its income increases.A few earlier studies provide evidence for this hypothesis (e.g., Alam et al., 1985; Sathaye and Tyler, 1991). Alam et al. (1985) found that income has a direct effect on household fuel-choice decisions. The higher the income level, the greater the tendency for households to choose commercial fuels over biomass fuels. Using a cross-section of 1000 sample households from Bangalore, India, Reddy (1995) examined household energy choices through a series of binomial logit models for different pairs of energy carriers. He confirmed the hypothesis of the energy ladder and the importance of income in household energy choices.

However, Reddy (1995) also argued that ‘as times change, societies become more egalitarian and this energy-ladder concept based on income may disappear’. In fact, the simple association between income and fuel choice has been criticized in recent literature. Fuel choice can be affected by a multitude of demographic and socio-economic factors (Davis, 1998; Masera et al., 2000; Barnett, 2000; Heltberg, 2005; Mekonnen and Köhlin 2008). A limited but increasing number of studies from the largest developing countries, such as India and China, provide evidence of the multiple factors that determine household fuel choice (e.g., Farsi el al., 2007; Jiang and O'Neil, 2004; Pachauri and Jiang, 2008). Household size, education and gender of the household head are found to be among the key determinants of fuel choice and transition.

Despite these findings, the existing empirical research in this area documents mixed results for some of these factors. For example, while Hosier and Dowd (1987) found that large households tend to move away from wood and toward kerosene, the finding of Ouedraogo (2006) indicates that small households are more likely to use LPG and less likely to use fuelwood. Unlike these two studies, Heltberg (2004) found insignificant effects of household size on fuel transition (switching). Similarly, the empirical evidence on the effect of prices or relative prices is also mixed. Leach (1992) found that relative fuel prices are less important for household's substitution of traditional biomass fuels by modern energy sources. Likewise, Zhang and Kotani (2012) found that coal and LPG prices do not exhibit substitution effects. Nonetheless, Heltberg (2005) and Gupta and Köhlin (2006) found significant cross-price effects between different fuel types. Regarding the effect of education, most studies found positive effect of education on the transition to high quality fuel (e.g., Heltberg, 2004 and 2005, Jiang and O'Neill, 2004; Farsi el al., 2007). Some studies also looked at effect of locations or regions (Hosier and Dowd, 1987; Leach 1992; Heltberg, 2004 and 2005). Contrary to the energy ladder hypothesis, recent literature documents that 'fuel switching' in developing countries is often not complete and is, in fact, a gradual process with many households often using multiple fuels; the reasons for multiple fuel use are varied, from supply security to cultural, social or taste preferences (Masera et al., 2000; Heltberg, 2005; Farsi et al., 2007; Mekonnen and Köhlin, 2008).

Many studies have analyzed the determinants of fuel choices in the developing world based on cross-sectional data (e.g., Hosier and Dowd, 1987; Leach, 1992; Farsi el al., 2007). Few studies have employed panel data (e.g., Mekonnen and Köhlin 2008). Regarding the studies on China, most of them are based on aggregate statistics, on surveys conducted in certain province or counties, or on rural households (Zhang and Kotani, 2012; Peng et al., 2010, Chen et al., 2006; Wang and Feng, 1997; ESMAP, 1996). Based on aggregate statistics and descriptive statistical tests, Cai and Jiang (2007) tested the energy ladder hypothesis by comparing the energy consumption pattern of rural households with that of urban households. Their results show that urban households use fuel that is more convenient, cleaner, and more efficient than that used in rural areas, where biomass and coal are common fuel. Peng et al (2010) studied household level fuel switching using cross-sectional data from rural Hubei. They found that fuel use varies enormously across geographic regions due to disparities in availability of different energy sources. Their results indicate thatrural households do switch to commercial energy sources, with coal as the principal substitute for biomass. Using household survey from rural Beijing, Zhang and Kotani (2012) found that coal and liquefied petroleum gas (LPG) prices do not exhibit substitution effects. While many of the studies are based on surveys conducted in certain provinces or villages,very few examined household energy choices through anationwide household survey.Jiang and O'Neil (2004) explored patterns of residential energy use in rural China by using a nationally representative rural household survey and various sources of aggregate statistics.

From the above empirical evidences on fuel choices in China and other developing countries we observe the following knowledge gaps. First, many of the existing studies in China are based on surveys in certain province or county and it is difficult to make generalizations from these studies. Second, most of the previous studies on household fuel choice in developing countries are based on cross-sectional data in which it is difficult to control for the unobserved individual heterogeneity. Our study seeks to fill these gaps.

3. Empirical strategy

Ordered probit and logit models are widely used for analyzing the discrete choice problem where responses can be considered ordinal. Ordered probit models have already been applied to household cooking fuel choices in the recent literature (e.g., Farsi el al., 2007). Compared with OLS regression, an ordered probit model is more appropriate for the analysis of household fuel choice if we believe that there is an ordinal rank for different types of fuels in terms of efficiency or convenience. To our knowledge, none of the studies using ordered probit models has analyzed household fuel choice by employing the ordered probit model with panel data application, where the unobserved individual heterogeneity can be better dealt with by exploring the panel structure of the data set.

The ordered probit model assumes that there is a latent variable which will determine a subject's choice. In the context of household cooking fuel choices, the ordered probit model begins with a latent variable:

$$E_{it}^{*} = x_{it}'\beta + \varepsilon_{it}, \quad \varepsilon_{it} \mid x_{it} \sim N(0,1) \tag{1}$$

The observed cooking fuel choices are assumed to be determined by the value of this latent variable:

$$E_{it} = j \text{ if } \mu_{j-1} < E_{it}^{*} < \mu_{j}, \; j = 0,1,2,\ldots J \text{ and } \mu_{-1} = -\infty, \; \mu_{J} = +\infty \tag{2}$$

where E_{it} represents the choice of cooking fuel for household $i = 1,...,n$ in time period $t = 1,...T$, which can be ordered in terms of efficiencyor convenience (e.g., $E = 0$ for firewood, $E = 1$ for coal, and $E = 2$ for LNG, etc.). x represents a vector of explanatory variables, including income and other household characteristics, β is the vector of parameter estimates for explanatory variables, and μ s denote the unknown threshold values to be estimated with β . Assuming the standard normal distribution of ε , the probability that household i chooses cooking fuel j would be:

$$P(E_{it} = j \mid x_{it}) = \Phi(\mu_{j} - x_{it}'\beta) - \Phi(\mu_{j-1} - x_{it}'\beta), \; j = 0,1,2,\ldots J \tag{3}$$

where $\Phi(\cdot)$ is the cumulative distribution function of standard normal distribution. The vector of parameter estimate β, along with the μ s, can be estimated through the maximum-likelihood estimation procedure. However, the standard ordered probit (logit) models implicitly impose the parallel regression assumption, which assumes the same slope for explanatory variables in different categories of dependent variables. In the context of household fuel choice, this implies that the effects of income and other household characteristics are assumed to have homogenous effects across different cooking fuels. However, this assumption can be too strong. For example, as noted above, the cost of moving from firewood to coal may not be the same as that for moving from coal to natural gas. To relax this assumption, we can employ a more flexible framework through a generalized ordered probit model, where the effects of income and other household characteristics across different cooking fuels are unrestricted. The generalized model rewrites Equation (2) as:

$$E_{it} = j \text{ if } \mu_{ij-1} < E_{it}^{*} < \mu_{ij},\ j = 0,1,2,\ldots J \text{ and } \mu_{-1} = -\infty,\ \mu_{J} = +\infty \qquad (4)$$

where $\mu_{ij} = \mu_j + x_{\mathrm{it}}'\lambda_j$. It can be seen that heterogeneity enters the generalized ordered model through the heterogeneity in threshold values μ_{ij} which are now assumed to be linear functions of the explanatory variables x_{it}. Consequently, the probability that household i chooses cooking fuel j in the generalized setting can be written as:

$$\begin{aligned} P(E_{it} = j \mid x_{it}) &= \Phi(\mu_{ij} - x_{\mathrm{it}}'\beta) - \Phi(\mu_{i,j-1} - x_{\mathrm{it}}'\beta) \\ &= \Phi(\mu_j - x_{\mathrm{it}}'\beta_j) - \Phi(\mu_{j-1} - x_{\mathrm{it}}'\beta_j) \end{aligned},\ j = 0,1,2,\ldots J \qquad (5)$$

where $\beta_j = \beta - \lambda_j$. Thus, we can see that the heterogeneity in the generalized model actually causes the vector of parameter estimates β_j to become category-specific (i.e., there are different parameter estimates for different fuel categories). The standard ordered probit model can be considered a special case of the generalized model with the imposition of the restriction $\beta_1 = \ldots = \beta_J$.

Usingpanel data, individual-specific random effectscan be incorporated into the model and Equation (1) can be rewritten as:

$$E_{it}^{*} = x_{it}'\beta + \alpha_i + \varepsilon_{it}, \quad \varepsilon_{it} \mid X_i \sim N(0,1) \tag{6}$$

It is assumed that, conditional on x_{it}, α_i is normally distributed with mean zero and variance σ_α^2, and is independent of ε_{it} and x_{it}. Under these assumptions, it can be shown that the correlation between the error term $\alpha_i + \varepsilon_{it}$ in any two time periods will be:

$$\rho = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_\varepsilon^2} \tag{7}$$

If $\rho \neq 0$, the random effect ordered probit model would be a significant improvement on the simple ordered probit model since it takes care of the serial correlation in the composite error term.

Using panel data, Equation (5) can be rewritten as

$$P(E_{it} = j \mid x_{it}, \alpha_i) = \Phi(\mu_j - \alpha_i - x_{it}'\beta_j) - \Phi(\mu_{j-1} - \alpha_i - x_{it}'\beta_j), \; j = 0,1,2,\ldots J \tag{8}$$

That is, the outcome probabilities are conditional on the individual effect α_i, which differs from the standard (cross-sectional) ordered probit model. Thus, the random effect α_i should be integrated out to get the likelihood of each individual's choice sequence and the maximum likelihood estimation procedure can be employed to estimate the random effect model. As we can see, the random effect generalized ordered probit model takes into account both the heterogeneous effects of explanatory variables across different fuels, which is ignored by the standard ordered probit model, and the unobserved individual heterogeneity, which is omitted in cross-sectional analysis.

4. Data

The longitudinal data used in this study come from the China Health and Nutrition Survey (CHNS), which is one of the most widely-used surveys for micro-level research in China. The CHNS was designed as a time-cohort survey. By now, eight waves of CHNS data have been collected (for the years 1989, 1991, 1993, 1997, 2000, 2004, 2006, and 2009). The survey employed a multistage, random cluster design to draw a sample of households, covering both rural and urban areas of nine Chinese provinces that vary substantially in socio-economic indicators[2]. Because data for the latest wave (for the year 2009) is not yet totally available, we

[2]The provinces are Liaoning, Heilongjiang, Jiangsu, Shandong, Henan, Hubei, Hunan, Guangxi, and Guizhou. See more details on the survey design at http://www.cpc.unc.edu/projects/china

focus our study on the first seven waves of the survey. Because this study concentrates on urban China, the rural households have been dropped from our sample.

In the CHNS survey, households are asked what kind of fuel(s) they normally use for cooking. Although households may not rely on just one type of cooking fuel, this study focused on the choice of primary cooking fuel, which is the fuel most often used, as stated in each household's response to the survey. Firewood (including wood, sticks, straw, etc.), coal, and LNG are found to be three of the most commonly used primary cooking fuels among the urban households and they account for up to 83% of the pooled sample. Thus, we focus on the choice among these three cooking fuels. Consequently our dependent variable – household cooking fuel choice – in the ordered probit model would be choice of firewood, coal, and LNG, which are in order of efficiency, convenience to use, and modernity. Therefore, we assign $E = 0$ for firewood, $E = 1$ for coal, and $E = 2$ for LNG as the dependent variable. This is similar to the order in Farsi el al. (2007), which considered the cooking fuels in urban India in the order of firewood, kerosene, and LPG.

Given that our study focused on analyzing the determinants of primary cooking energy choice, we eliminated the observations for which important variables (including the primary cooking fuel choice, household income, energy price data, characteristics of household head, etc.) are not available. This produces our final sample of 3425 pooled observations.

From this sample, we find that the percentage of households using LNG as their primary cooking fuel increased dramatically over time, while the percentage of households using firewood or coal shows a clear tendency of decreasing. This implies households' transition toward more efficient sources of primary cooking energy in urban China. For instance, the data indicate that, in 1989, around 75% of urban households used coal as their primary cooking fuel. This figure decreased dramatically to 45.7% in 1997 and declined further to 26% in 2006. The proportion of households choosing firewood as their primary cooking energy decreased from 11.3% in 1989 to only 7% in 2006. At the same time, the proportion of households using LNG as their primary cooking fuel increased from 13.2% in 1989 to 44.7% in 1997 and rose further to 67% in 2006. These facts seem to suggest a tendency of switching in households' preference of primary cooking fuels to more efficient energy.

We studied the effect of household income because that has been found in the literature to be an important determinant of household fuel choice. The household income used in this study is already inflated to the year 2009, using Consumer Price Indexes, to make income comparable over different time periods (waves) and is included in the CHNS data set. The relationship between primary cooking fuel choices and household income level is presented in Figure 1. It can be seen that, as household income increases, people are more likely to choose the fuels that are ranked higher in terms of efficiency or modernity, i.e., LNG, as their primary cooking fuels, and are less likely to choose the fuels that are ranked lower, like firewood and coal.

< Figure 1 here>

Table 1 presents the descriptive statistics for socioeconomic variables by cooking fuel choices. It can be observed from Table 1 that some trends exist in households' choice of primary cooking fuel. As well as household income, gender, education and job characteristics of household heads are associated with distinct differences between households who choose firewood as their primary cooking fuel and those who choose LNG as their primary cooking fuel. For instance, the average income for the households who choose LNG as their primary cooking fuel is over 70% higher than those who prefer firewood. Further, the proportion of female household heads in the 'LNG' category is larger than that in the 'firewood' category or that in the 'coal' category.

Three dummy variables were used to represent the highest education attained by household heads: primary school degree, secondary school degree, and university (or higher) degree. As shown in Table 1, only 0.3% of the heads of the households choosing firewood as their primary cooking fuel have a university or higher degree, while the figure is about 9.7% for those choosing LNG. Though the differences in primary school degree achievement are not as remarkable as those for the university degree, we can still observe that the proportion of household heads who only completed primary schooling is higher in the ‘firewood’ category. Also, it can be seen that a higher share of household heads have a secondary school degree in the ‘LNG’ category, compared with the ‘firewood’ or ‘coal’ category. All these facts seem to suggest that better educated people tend to choose more efficient fuels.

The job characteristic of a household head is represented by a dummy variable indicating whether the head was employed in the public sector[3] by the time of survey. The differences related to this variable can also be clearly observed in Table 1. Specifically, only 11.6% of the household heads who choose firewood as the primary cooking fuel are employed in the public sector, whereas the figure is 35.8% for the household heads choosing coal and 37.5% for the household heads choosing LNG. This indicates a possible relationship between public sector employment and household cooking fuel choice. In terms of household size, the descriptive statistics show that the households choosing LNG as their primary cooking fuel tend to be smaller on average, compared with those choosing firewood or coal as their primary cooking fuel.

< Table 1 here>

In the literature, fuel prices have also been found to be potential determinants of household cooking fuel choices. Because the prices of firewood (wood, straw, etc.)are not available in the survey, only the prices of coal and LNG are considered in the final analysis. Moreover, the

[3] The public sector here includes government departments, state service/institutes, and state-owned enterprises.

fuel prices in the survey are at the community level, which implies that all the households in one community face the same price. In addition, the prices of coal and LNG are inflated to the year 2009 to make them comparable over different time periods (waves). The variables used in the econometric analysis that follows are listed in Table 2, where the descriptive statistics are for the entire sample.

< Table 2 here>

5. Empirical Results

Results from the maximum likelihood estimation for the standard ordered probit (OPROBIT), generalized ordered probit (GOPROBIT), and random effect generalized ordered probit (RE-GOPROBIT) models[4] are presented in Table 3. To control for the time trend of the panel data and regional differences in fuel choices, we include wave and area (province) dummies in all the regressions. From Table 3, it can be seen that, in each generalized model, two parameter-vectors (β_1 and β_2) are estimated. The parameter vector β_1 refers to estimated coefficients of the determinants for the coal category compared to the base category (firewood). Vector β_2 is for LNG. The explanatory variables used in all these regressions are displayed in Table 2.The marginal effects of significant variables on the probability of choosing each fuel as the

[4] The generalized ordered probit model and random effect generalized ordered probit model were estimated in Stata using the commands 'goprobit' and 'regoprob', respectively.

primary cooking fuel, evaluated at the sample mean, are presented in graphical form for the sake of brevity, as shown in Figures 2a, 2b, and 2c.

One cannot directly interpret the estimated coefficients from each of three ordered probit models because the true parameters of each model are confounded by a scale parameter. However, the comparisons of parameter estimates in terms of sign and significance are useful for understanding our results. By looking at the estimated results of the three ordered probit models in Table 3, we can see some differences in size and signs of the estimated coefficients for some of the explanatory variables across the three models. For instance, the coefficient for coal price shows a large difference between the estimates from OPROBIT and those from GOPROBIT. The coefficients for coal price in the two parameter-vectors (β_1 and β_2) of GOPROBIT have opposite signs and their magnitudes are nearly twice as large as the estimate from OPROBIT. The positive sign of the estimated coefficient for coal price in the OPROBIT implies that a higher price of coal induces households to choose higher ranked fuel(s). The parallel regression assumption of the OPROBIT model implies that the effects of coal price would be the same for different fuel categories. Yet, from the GOPROBIT results,one can see that this may not be the case. More specifically, the different signs of the coefficients of coal price in the two parameter-vectors of GOPROBIT are manifestations of the heterogeneous effect of this variable on household's fuel preference ordering. A similar pattern is observed in the price of LNG. However, this does not apply for all variables. For instance, with respect to household income, GOPROBIT estimates are only slightly different from the OPROBIT estimates.

< Table 3 here>

While the results from OPROBIT and GOPROBIT can give some preliminary information on the factors that may affect the choices of cooking fuels, they are generally considered inefficient and inconsistent due to the potential unobserved individual heterogeneity, which can be addressed in the RE-GOPROBIT results. Comparing GOPROBIT and RE-GOPROBIT results, we can see some observed differences in the size for some of the explanatory variables. For example, the coefficient on the coal price variable in the parameter vector β_1 is larger in RE-GOPROBIT than the estimate in GOPROBIT. On the other hand, the estimated coefficient on the household income in the parameter vector β_1 is also different between GOPROBIT and RE-GOPROBIT. A Wald test on each of the generalized ordered probit models against the standard ordered probit model suggests that we can reject the null hypothesis of equal slope parameters (χ^2_{26}=597.25 for GOPROBIT and χ^2_{26}=422.58 for RE-GOPROBIT) and implies the existence of the heterogeneous effect of explanatory variables across different fuels. Moreover, in the random effect regression, the coefficient of ρ (0.4904) is significantly different from zero (p-value=0.000), which indicates the important role of unobserved heterogeneity. These results of the Wald test and the coefficient of ρ clearly indicate the necessity for generalized ordered probit models and panel data analysis in estimating fuel choice from this perspective. Considering this, we refer mainly to the RE-GOPROBIT results and the corresponding marginal effects in our discussion that follows.

From all these regression results, it is evident that household economic status, head's characteristics, fuel prices and year (wave) dummy variables play an important role in determining the household's primary cooking fuel choice in urban China. Beginning our analysis with the economic status of the household, one can see from Table 3 that this variable is positive and significant in the two parameter-vectors (β_1 and β_2) of the RE-GOPROBIT columns. These two positive estimates convey the message that, as the income of households rise, they prefer to use coal and LNG rather than firewood as their primary cooking fuels. Nonetheless, the marginal effect of household income is negative for the probability of choosing coal but positive for the probability of choosing LNG, when evaluated at the sample mean. This implies that households prefer LNG to coal as income increases. In general, a one unit increase in household income (log) will on average decrease the probability of choosing firewood and coal by 1% and 5.1%, respectively, while increasing the probability of using LNG by 6.1%. The marginal effect results from OPROBIT and GOPROBIT also suggest the negative effects of income on the choice of firewood or coal and the positive effect of income on LNG, as can be seen in the Figures 2a, 2b and 2c. The general finding that households' preferences for higher ranked energy sources increase as their income rises is consistent with findings from earlier studies (Heltberg 2004, 2005; Farsi el al. 2007; Mekonnen and Köhlin, 2008).

< Figures 2a, 2b, 2c here>

Consistent with previous studies (Heltberg 2004, 2005; Farsi el al. 2007; Mekonnen and Köhlin, 2008; Gebregzabiher 2012), fuel prices are also found to be important in determining cooking energy choices in urban China. As we can see from the results of RE-GOPROBIT in Table 3 and its corresponding marginal effect diagrams (Figures 2a, 2b and 2c), a higher coal price decreases the probability of choosing coal as the primary cooking energy and increases the probability of choosing firewood and LNG. More specifically, a one unit increase in the coal price (log) will decrease the average share of households choosing coal as their primary cooking fuel by 5.4%, while increasing the share of those choosing firewood and LNG by 0.6% and 4.8%, respectively. We can see similar results from GOPROBIT estimates. However, in the standard ordered probit model (OPROBIT), a higher coal price is found to be associated with a lower possibility of choosing firewood. The difference may reflect the fact that the OPROBIT model does not take into account potential heterogeneous effects of the explanatory variables across fuels, while the generalized models do.

An increase in LNG price, on the other hand, deceases households' choice for LNG (own price effect) but increases their choice of coal or firewood (substitution effect). It can be observed from the RE-GOPROBIT marginal effect diagrams (Figures 2a, 2b and 2c) that a one unit increase in the LNG price (log) will increase the average share of households that choose coal as the primary cooking fuel by 12.7%, while decreasing the share of those choosing LNG by 11.9%. But the marginal effect of such an increase in the LNG price on the probability of choosing firewood is insignificant, even though the sign is negative. Similar to the coal price effect discussed above, we also see a different result in the standard ordered probit model, where a higher LNG price is shown to have a positive marginal effect on the probability of choosing firewood; this marginal effect is statistically insignificant at the conventional level in both generalized models (GOPROBIT and RE-GOPROBIT). The estimate results for the fuel price variables imply that price policies can play an important role in households' fuel transitions. Policies that decrease the prices of modern energy sources can have positive effects in reducing deforestation as well as indoor air pollution and its health impacts.

In many developing countries, it is more common to see women than men cooking, and hence they are more likely to be exposed to the health hazards of indoor air pollution from using dirty fuel sources. Our expectation is that, compared to the male headed households, the decision-makers in female headed households understand better the health risks and inconveniences of cooking with unclean fuel sources. Consistent with our expectation, all three models suggest that female headed households are less likely to choose firewood or coal as their primary cooking fuel, and more likely to choose LNG. Referring to the marginal effect results of the RE-GOPROBIT model, female headed households are, on average, 14.1% more likely to choose LNG as their primary cooking fuel, 1.9% less likely to choose firewood, and 12.2% less likely to choose coal than are households with male heads. This implies that greater empowerment of women in the household can be helpful in increasing the usage of cleaner household energy in China.

In addition, the job characteristics of a household head can also affect the household's preference for cooking fuel choices. Our results show that households with heads employed in the public sector will also tend to choose LNG as the primary cooking fuel, and are less likely to choose firewood or coal; these results are supported by all of these three models. Referring to the results from RE-GOROBIT model, for instance, the probability of choosing LNG as the primary cooking fuel will be 18% higher, on average, for households which have heads working in the public sector, while the probability of choosing firewood and coal will be 2 % and 16% % lower, respectively, for these households.

In addition, education is an important policy tool to raise households' awareness about the benefits of clean energy sources and the risks of dirty fuel sources. This implies that educated households are expected to be more likely to choose clean energy sources. In this study, we use three dummy variables to represent the highest education attained by household heads: primary school degree, secondary school degree, and university (or higher) degree. Consistent with our expectation, households heads having a primary school degree or higher are more likely to choose higher ranked energy sources than those who do not have a primary degree. More specifically, household heads having a primary degree are only slightly more likely to choose clean energy (LNG) than those with no primary school degree. However, the effect is stronger with secondary and higher levels of education. From the marginal effect results of RE-GOPROBIT illustrated in Figures 2a, 2b, and 2c, household heads having a secondary school degree are on average 1.8% less likely to choose firewood as the primary cooking fuel and 18.4% less likely to choose coal, but 19.9% more likely to choose LNG, compared with those without a primary school degree. Moreover, compared with the household heads without a primary school degree, those having a university (or higher) education will be on average 2% less likely to choose firewood as the primary cooking fuel and 37.8% less likely to choose coal, but 39.8% more likely to choose LNG. With a closer look at these marginal effects, we can see that a higher education will have a larger effect on reducing the probability of choosing firewood or coal and increasing the probability of choosing LNG. This effect of education is consistent with earlier studies on fuel demand (Jiang and O'Neil (2004), Heltberg 2004, 2005; Farsi el al. 2007; Mekonnen and Köhlin, 2008).

Previous studies find mixed results on the effect of household size on fuel choice and fuel switching (Heltberg 2004, 2005; Ouedraogo, 2006; Farsi el al. 2007). For example, Ouedraogo (2006) suggests that, in urban Burkina Faso, households with fewer members are more likely to adopt LPG and less likely to use firewood for cooking. However, Heltberg (2004) found insignificant effect of household size on fuel switching. Consistent with the finding of Ouedraogo (2006), our results suggest that a larger household size is associated with a higher probability of choosing firewood as the primary cooking fuel and a lower probability of choosing LNG. Using the marginal effect results from RE-GOPROBIT, increasing the household size by one more person is associated with a 0.5% increase in the probability of choosing firewood as the primary cooking fuel and a 1.8% decrease in the probability of choosing LNG on average, while the marginal effect on the probability of choosing coal is insignificant. This may suggest that clean cooking energy like LNG can be more easily adopted in a smaller household.

Ordered probit models assume the ordering of different fuels in terms of efficiency and convenience to use. However, the real process of decision-making for choosing fuels is not known to econometricians, and households may make fuel choice decisions without considering the ordering of fuels in terms of efficiency or convenience. Taking this into account, we also used the standard and random effect multinomial logit models to estimate the determinants of household fuel choice in urban China[5]. Results of these models (Table 4) can be compared to the results of the ordered probit models in order to check their robustness. Similar to the ordered probit models, the parameter vector β_1 refers to estimated coefficients

[5] We used Stata codes "gllamm" to estimate the multinomial logit model with unobserved heterogeneity.

of the determinants for the coal category compared to the base category (firewood), and vector β_2 refers to LNG.

< Table 4 here>

One can see from Tables 3 and 4 that, in both types of models, household income is positive and significant, implying that households choose higher quality fuel sources as their income increases. We can also see similar results with respect to household size, LNG price, age, gender, and area dummies. Given these results of multinomial logit models, which suggest that households' tendency for choosing higher quality fuels as their primary cooking fuels will be higher with increased income, lower prices, lower households' size, etc., the results from the generalized ordered probit models above seem to be robust.

6. Conclusion and policy implications

Households' transition to modern energy sources can reduce the health and environmental impacts caused by the usage of traditional energy. Understanding the determinants of household fuel choice can provide policy implications for encouraging the adoption of cleaner and more efficient fuels in households. As the largest developing country in the world, China's evidence on this issue is of great interest. Different from the previous studies on China, most of which are based aggregate statistics or cross-sectional data from household surveys on certain regions, this paper employed the panel data from a nationwide survey

(CHNS) to study the determinants of household fuel choice in urban China. Ordered probit models were employed in this study to take into account the potential ordering of different fuels in terms of efficiency or convenience to use, as in Farsi el al. (2007). Moreover, we made extensions to the applications of ordered discrete choice models to household fuel choice. First, considering the potential heterogeneous effects of explanatory variables across different fuels, this paper employed the generalized ordered probit models rather than the standard ordered probit model. Second, to explore the panel structure of the data set, the random effect generalized ordered probit model was chosen to analyze household cooking fuel in urban China.

The importance of household income in determining household choices for cooking energy is supported by our study on urban China. Higher income leads to a lower probability of choosing firewood or coal as the primary cooking fuel but is associated with a higher probability of choosing LNG, which is more efficient than the other two kinds of fuels. Meanwhile, the results also show that, in addition to income, there are several socio-demographic factors, such as gender, occupation, and education of the household heads, which are also important in determining the choices of primary cooking fuels in urban Chinese households. Thus, consistent with other recent studies (Heltberg, 2005; Masera et al., 2000; Farsi et al., 2007), our results suggest that household fuel choice is not determined merely by household's economic condition.

Coal and LNG prices were also found to be important in household choices of primary cooking energy. An increase in the coal price is associated with a statistically significant decrease in the probability of choosing coal but a significant increase in the probability of choosing LNG or firewood as the primary cooking fuel. And, as expected, a higher LNG price will reduce the probability of choosing LNG and increase the probability of choosing coal for the primary cooking fuel. From a policy point of view, these results indicate that interventions that reduce the price of LNG can encourage household to use it as the primary cooking fuel and reduce the usage of dirty fuels.

The tendency that households with female heads are more likely to choose LNG as the primary cooking fuel and to reduce the usage of firewood or coal implies that greater empowerment of women in the household can be helpful in increasing the usage of clean energy in urban China. In addition, the results that more education for household heads generally reduce the probability of choosing firewood or coal, while increasing the probability of choosing LNG, suggest that promotion of higher levels of education can be an effective way to encourage households to choose clean energy as the primary cooking fuel.

However, this paper is not without limitations. For example, due to lack of information on the proportion of each fuel for the households who use multiple fuels, this study focused on the choice of primary cooking fuels and did not analyze multiple fuel use. Therefore, a direction for future research can be more comprehensive modeling of households' decision making on cooking fuels with consideration of all the fuels that a household can use. This will require richer data on households' cooking fuel choices.

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Table 1. Means of major variables by primary cooking fuel choice

	Firewood E=0	Coal E=1	LNG E=2
Household income	15149.99	18547.94	26436.44
Age of household head	49.892	53.257	52.990
HHs with a female head	0.143	0.252	0.271
HH head married	0.874	0.840	0.858
HH head employed in public sector	0.116	0.358	0.375
HH head with primary education	0.214	0.218	0.163
HH head with secondary education	0.415	0.394	0.547
HH head with university (or higher) educ.	0.003	0.018	0.097
HH size (number of persons in HH)	4.051	3.627	3.270

Table 2. Descriptive statistics

Variable	Mean	Std. Dev.	Minimum	Maximum
Household income	21975.950	24185.540	5.160	412145.700
Coal price	0.541	0.788	0.035	4.674
LNG price	78.582	19.466	26.076	127.800
Age of household head	52.843	14.106	12.290	97.110
HHs with a female head	0.251	0.434	0	1
HH head married	0.851	0.356	0	1
HH head employed in public sector	0.345	0.476	0	1
HH head with primary education	0.192	0.394	0	1
HH head with secondary education	0.468	0.499	0	1
HH head with university (or higher) educ.	0.054	0.227	0	1
HH size (number of persons in HH)	3.495	1.384	1	12

Table 3. Estimation results of ordered probit (OPROBIT), generalized ordered probit (GOPROBIT) and random effect ordered probit (RE-GOPROBIT) models

Dependent variable: cooking fuel choice	OPROBIT	GOPROBIT		RE-GOPROBIT	
		β_1	β_2	β_1	β_2
Household income (log)	0.201***	0.293***	0.213***	0.327***	0.216***
	(0.0259)	(0.0435)	(0.0290)	(0.0579)	(0.0385)
Coal price (log)	0.0590**	-0.160***	0.127***	-0.212**	0.170***
	(0.0268)	(0.0526)	(0.0322)	(0.0829)	(0.0439)
LNG price (log)	-0.302**	0.0888	-0.361**	0.268	-0.421**
	(0.125)	(0.261)	(0.153)	(0.392)	(0.201)
Age of household head	0.0101	0.0207	-0.00424	0.0362	-0.00455
	(0.0119)	(0.0210)	(0.0136)	(0.0265)	(0.0187)
Age squared/100	-0.00200	-0.00552	0.00992	-0.0173	0.0107
	(0.0110)	(0.0195)	(0.0125)	(0.0243)	(0.0171)
HHs with a female head	0.351***	0.720***	0.342***	0.827***	0.498***
	(0.0678)	(0.159)	(0.0738)	(0.171)	(0.103)
HH head married	0.00267	0.206	-0.0326	0.110	-0.0217
	(0.0790)	(0.166)	(0.0898)	(0.194)	(0.121)
HH head employed in public sector	0.587***	0.888***	0.589***	0.913***	0.644***
	(0.0581)	(0.106)	(0.0707)	(0.150)	(0.0932)
HH head with primary education	0.0928	0.0771	0.160**	0.109	0.197*
	(0.0689)	(0.125)	(0.0812)	(0.162)	(0.116)
HH head with secondary education	0.381***	0.395***	0.506***	0.609***	0.720***
	(0.0721)	(0.132)	(0.0817)	(0.156)	(0.115)
HH head with university (or higher) educ.	1.025***	1.289***	1.114***	1.946***	1.584***
	(0.153)	(0.392)	(0.165)	(0.597)	(0.228)
HH size (number of persons in HH)	-0.0956***	-0.135***	-0.0802***	-0.170***	-0.0644**
	(0.0195)	(0.0342)	(0.0218)	(0.0418)	(0.0300)
_Iwave_1991	0.373***	0.00865	0.586***	-0.352	0.755***
	(0.0787)	(0.220)	(0.114)	(0.304)	(0.184)
_Iwave_1993	0.410***	0.0525	0.732***	0.0488	1.150***
	(0.0827)	(0.157)	(0.126)	(0.245)	(0.189)
_Iwave_1997	0.674***	-0.162	1.232***	-0.329	1.767***
	(0.0923)	(0.177)	(0.135)	(0.281)	(0.198)
_Iwave_2000	0.884***	0.330**	1.352***	0.345	1.976***
	(0.0838)	(0.157)	(0.124)	(0.243)	(0.191)
_Iwave_2004	0.972***	0.668***	1.414***	0.690**	2.029***
	(0.0963)	(0.185)	(0.136)	(0.272)	(0.205)
_Iwave_2006	1.182***	0.585***	1.633***	0.640**	2.345***
	(0.108)	(0.196)	(0.142)	(0.273)	(0.217)
Province dummies	Yes	Yes		Yes	
Log likelihood	-2544.5269	-2119.6083		-2022.9301	
Observations	3425		3425		3425

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 4. Estimation results of standard and random effect multinomial logit model

	Multinomial		Random Multinomial	
Dependent variable: cooking fuel choice				
	β_1	β_2	β_1	β_{21}
Household income (log)	0.503***	0.803***	0.301***	0.597***
	(0.151)	(0.152)	(0.0917)	(0.0966)
Coal price (log)	-0.328	-0.0901	-0.366***	-0.131
	(0.209)	(0.209)	(0.105)	(0.105)
LNG price (log)	-2.412**	-2.994***	-0.573	-1.221**
	(1.002)	(1.005)	(0.533)	(0.551)
Age of household head	0.0732	0.0562	0.0513	0.0395
	(0.0703)	(0.0706)	(0.0413)	(0.0413)
Age squared/100	-0.0241	-0.00398	-0.0214	-0.00657
	(0.0652)	(0.0655)	(0.0385)	(0.0383)
HHs with a female head	1.456***	1.879***	1.034***	1.414***
	(0.420)	(0.420)	(0.299)	(0.306)
Marriage status of household head	0.327	0.235	0.444	0.327
	(0.443)	(0.446)	(0.338)	(0.332)
HH head employed in public sector	1.808***	2.623***	1.382***	2.166***
	(0.405)	(0.406)	(0.236)	(0.252)
HH head with primary education	0.214	0.463	0.0484	0.277
	(0.406)	(0.410)	(0.248)	(0.259)
HH head with secondary education	0.456	1.308***	0.0978	0.914***
	(0.423)	(0.425)	(0.294)	(0.293)
HH head with university (or higher) educ.	2.868*	4.662***	1.271	3.037***
	(1.691)	(1.678)	(1.078)	(1.054)
HH size (number of persons in HH)	-0.266**	-0.373***	-0.160**	-0.269***
	(0.108)	(0.109)	(0.0655)	(0.0693)
_Iwave_1991	-0.790	0.0351	0.597	1.422***
	(0.708)	(0.728)	(0.458)	(0.483)
_Iwave_1993	-0.673	0.406	0.121	1.243***
	(0.567)	(0.596)	(0.297)	(0.334)
_Iwave_1997	-2.134***	-0.0525	-1.001***	1.041***
	(0.676)	(0.698)	(0.347)	(0.384)
_Iwave_2000	-0.712	1.551***	-0.0154	2.229***
	(0.575)	(0.598)	(0.291)	(0.325)
_Iwave_2004	-0.160	2.202***	0.225	2.592***
	(0.625)	(0.648)	(0.331)	(0.357)
_Iwave_2006	0.407	3.141***	0.196	2.932***
	(0.665)	(0.683)	(0.379)	(0.398)
Province dummies	Yes		Yes	
Log likelihood	-2123.1699		-2045.2572	
Observations	3,425		3,425	

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

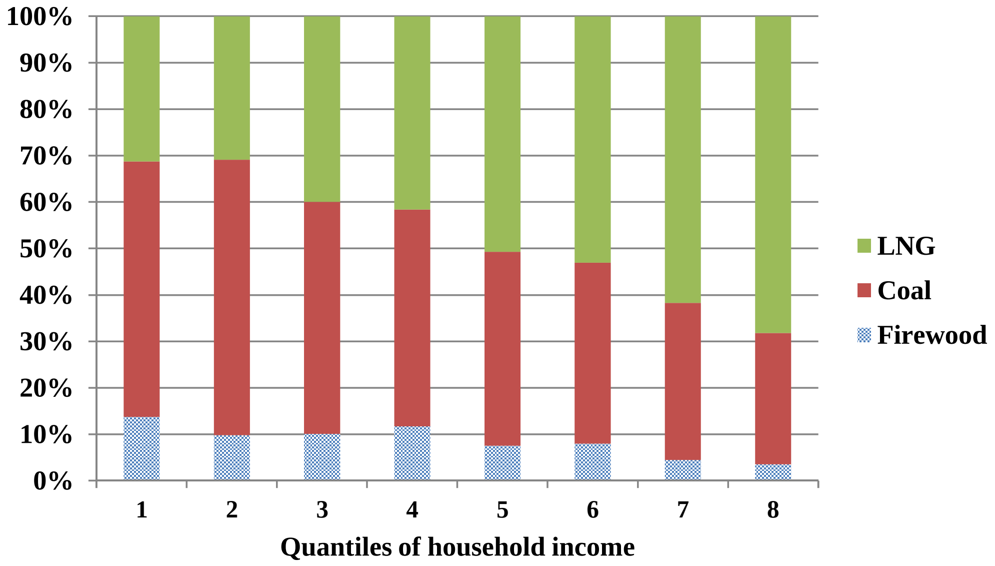
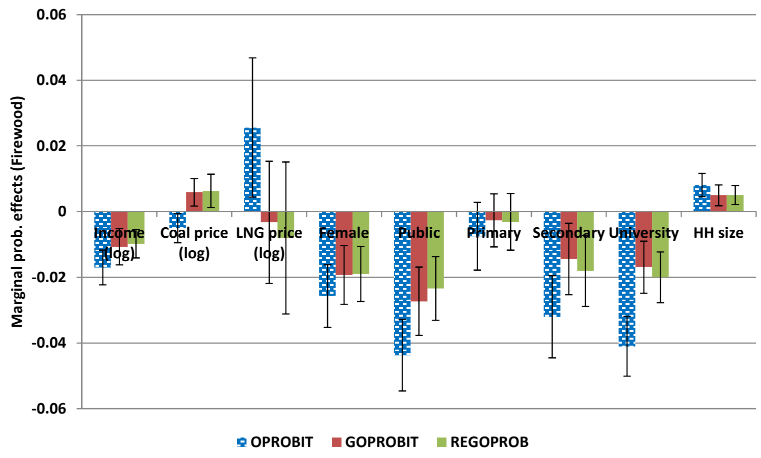
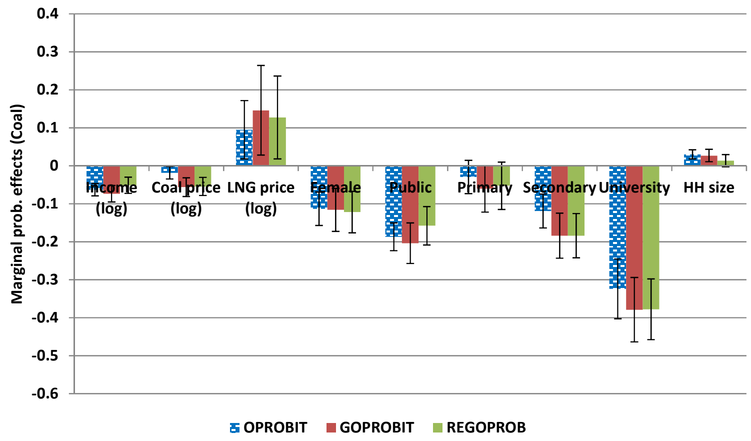


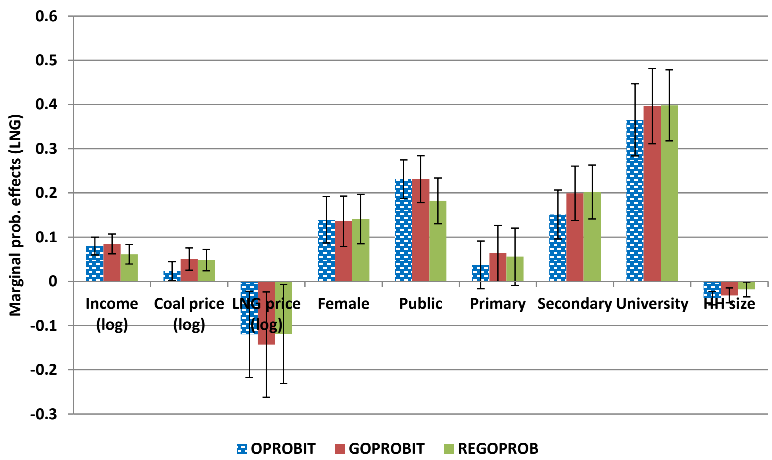
Fig. 1. Primary cooking fuel by quantiles of household income



a. Marginal effects on the probability of choosing firewood as the primary cooking energy



b. Marginal effects on the probability of choosing coal as the primary cooking energy



c. Marginal effects on the probability of choosing LNG as the primary cooking energy

Fig.2. Marginal effects obtained from different models