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# Household Energy Choices and Fuelwood Consumption: An Econometric Approach to the French Data

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# Household Energy Choices and Fuelwood Consumption: An Econometric Approach to the French Data[*]

Stéphane Couture[♦], Serge Garcia[•] et Arnaud Reynaud[□]

**Abstract:**

In an international context of soaring oil prices and growing awareness of the need to combat global warming, wood would appear to be becoming increasingly competitive and desirable for our environment. France is the leading consumer of fuelwood in the EU, mainly for home consumption and for heating, although the share of wood in primary energy consumption is still very low (4%). It is therefore important to understand how domestic consumer fuelwood demand is determined. We propose an econometric analysis of fuelwood consumption by modeling the choice made by consumers of the type of use of wood for heating, and the possible combination between one energy used as a main source of heating and another used as a back-up. Our estimations show that this choice is mainly determined by income. Wood is chosen as the main energy source by the poorest households. Consumption is price sensitive in the case of main use of wood (price elasticity of -0.4), but price elasticity is lower in the case of back-up use, and varies according to the type of energy used as the main source (electricity, gas, fuel oil).

**Keywords:** energy wood, type of use, domestic demand, multinomial Logit, selection bias

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## I. Introduction

Faced with sharp fluctuations in fossil energy prices, wood for energy is becoming increasingly competitive and attractive for a number of reasons. Firstly, unlike fossil fuels, wood is a renewable energy resource whose availability is increasing, in particular in Europe.[1] Secondly, the use of energy from wood does not contribute to global warming. Although it emits carbon dioxide on combustion, wood is also a natural source of carbon dioxide absorption through forest growth. In the face of increasing environmental concerns, wood is a perfect substitute for polluting fossil fuels. Finally, forestry to produce wood for energy creates more jobs than are generated by other forms of energy.[2]

However, the share of fuelwood in world energy consumption remains low, currently representing just 15% of consumption (ADEME, 2004). With a view to combating climate change and diversifying energy sources, the European Commission is encouraging the member countries of the European Union (UE) to make greater use of renewable energies in the light of local production potential and sustainable availability. Within this framework, it has set an objective for the year 2010 of reaching a figure of 12% of energy consumption in Europe from biomass, and notably of forest origin.[3] Currently in the EU, the proportion of wood in total energy consumption is just 3.2%. Mainly through domestic consumption, France is the leading consumer of fuelwood, with 4% of its primary consumption for heating purposes. Wood used for home heating represents 20% of current consumption. The volume of fuelwood represents 35 million cubic metres a year, of which 20 million of forest origin and 15 million from by-products of the wood industry and farming (SOLAGRO, 2006). Present fuelwood consumption in Europe remains low compared with the targets set by the European Commission, and the period 1970-2005 has seen sharp variations in wood energy consumption, largely related to changes in household domestic use behaviour. These variations seem to be due just as much to the behaviour of consumers in the face of

[1] According to the UNECE/FAO (2005), long-term forest resource trends show that the area of forest, stands and rate of increment have been increasing regularly in Europe over the last few decades. In most European countries, the expansion of forest surface area is continuing, notably to occupy areas abandoned by farming. Also, the rate at which forests are growing in Europe is higher than that of annual felling, and the gap between the two has widened since 1960. On average, for the whole of Europe, the felling/increment ratio is somewhere around 45%.

[2] According to the Bianco report (1998), for one tonne of oil equivalent, fuelwood can create three times more jobs than fossil fuels such as imported gas or fuel oil.

[3] In France, this measure was backed up in 2005 by the Programming and Orientation Law (known as the "Pope" Law) aiming to achieve these ambitious objectives. This law sets the outlines of French energy policy to use biomass for energy: to produce 21% of electricity consumption from renewable resources by 2010, and to

environmental problems as to fluctuations in fossil energy prices and uncertainties as to the climate. The latest statistics on a constant climate basis show consumption down 8% on the thirty-year average.

Therefore, to achieve the targets that have been set, forests must produce more fuelwood than is currently the case and consumption must increase. In this respect, various incentives (equipment subsidies, tax credits, reduced-rate VAT) have already been introduced. However, before bringing in economic incentive instruments, it is important to be aware of the factors that explain the use of wood as a source of energy, in particular for domestic heating (which represents about 80% of fuelwood consumption in France). There are no such studies to date. This is the reason behind this article aiming to provide an empirical analysis of household fuelwood consumption and the determinants of the choice to use this energy for heating.

Household fuelwood consumption has mainly been studied in developing countries (Hosier and Dowd, 1987; Leach, 1992; Smith et al., 1994; Masera et al., 2000; Ouedraogo, 2006; Gupta and Köhlin, 2006). Rare are the studies covering fuelwood demand in developed countries (Hardie and Hassan, 1986; Mackenzie and Weaver, 1986; Vaage, 2000),[4] and there have been none at all in France focusing precisely on this issue, as far as we know. Most of the studies on developing countries focus on the problem of energy substitution between the four available sources (wood, gas, electricity and fuel oil). They are based on a hypothesis of energy substitution driven largely by economic factors (mainly income) explaining the choice of energy type and the quantity consumed by the household. This hypothesis is based on the fact that the energy technology used by the household is a function of its socio-economic status. The authors then study the relationship between energy demand, price and income. Most of these studies conclude that as household income increases, the so-called “old or traditional” energies (wood and fuel oil) are replaced by so-called “modern” technologies (gas and electricity). Using econometric approaches based either on discrete choice models or continuous models, the most recent studies applied to developing countries (Masera et al., 2000; Heltberg, 2005; Ouedraogo, 2006; Gupta and Köhlin, 2006; Farsi and Filippini, 2007) generalise this result by highlighting the importance of the role played by socio-demographic and sometimes cultural characteristics in choosing and determining main and secondary

increase heat production of renewable origin by 50% by 2010.

[4] Unlike the other studies carried out in developed countries, Steininger and Voraberger (2003) propose a calculable general equilibrium model enabling systematic comparison of the various available options to increase energy from biomass supplies (fuelwood, biosolid, biomethane and biofuel) for the production of heating, electricity and/or fuel.

energy sources, on top of the relationship between price, demand and income. In this way, energy consumption is determined by the characteristics of the households and the fuels (which are determined outside the household).

Studying energy demand (electricity, fuel oil, gas, wood) of Norwegian households for heating, Vaage (2000) used the discrete-continuous model proposed by Dubin and McFadden (1984) to demonstrate the dependence of energy demand on possession of (energy-consuming) appliances by the household. Energy consumption was shown to depend on choices of energy-powered devices such as heating, cooking and washing equipment. As the two decisions are linked, the choice of equipment was modelled jointly with energy demand to avoid selection bias. The study showed that income had a significant impact on choice probability, but not on energy consumption. Also, it came up with relatively high price elasticity (-1.29 and -1.24, depending on the model), explaining this result by the fact that the majority of households are equipped with mixed heating systems.

Mackenzie and Weaver (1986) focused their attention on fuelwood consumption in the United States. They used the two-stage model proposed by McFadden (1973) to model fuelwood demand. Using a Logit model, they estimated the probability of a household using fuelwood, and then corrected the selection bias in the estimation of wood demand. They came up with a negative relationship between price and wood consumption (with low price elasticity of -0.08), and between income and wood consumption. Although the authors did integrate the decision to choose fuelwood in studying wood consumption, they did not make a distinction between the different options relating to the use of such energy. Fuelwood can be seen as being a main or secondary source of heating (back-up heating or energy purely for pleasure: some households burn wood in their fireplace purely for pleasure and comfort). As far as we know, combinations between a main source of energy (electricity, gas, fuel oil) and wood have not been modelled. However, this type of use does determine wood consumption and must be taken into account explicitly in estimating demand functions. Observable and unobservable factors therefore determine the choice to use wood and also condition energy wood consumption levels of households. Failing to take this choice into account can result in selection bias.

In this article, we performed an econometric analysis of fuelwood consumption of households in order to estimate their demand functions, identify their determinants and measure price elasticities and income elasticities. On the one hand, we studied the profile of individuals according to their attitude to fuelwood and the way they see this resource as a source of energy and, on the other hand, we determined whether the economic variables (price, income) were explanatory factors of the decisions made by households in terms of energy choices (wood versus other energies, in the case at hand). We then made the distinction between three categories of fuelwood use: non-users, users for whom it is a main source of heating energy and users for whom it is a back-up energy source. Making the distinction between these categories of use before any analysis of consumption is performed can show that certain characteristics that have an impact on the type of wood use also affect consumption levels. For example, it could be thought intuitively that households using wood as their main heating energy will be much more sensitive to the price of the resource that households wanting just a "nice warm fire". The household is in fact faced with two simultaneous decisions. As the consumption of fuelwood is linked to the choice of fuelwood use category, estimating the fuelwood demand equation can introduce selection bias. To correct this bias, we began by estimating the multiple choice equation by a multinomial Logit multinomial, then the demand equations using the results of the first stage (demand error expectation conditional on errors in the latent choice model). We used the econometric methods proposed by Lee (1983), Dubin and McFadden (1984), noted DMF hereafter, and Dahl (2002) adapting the work of Heckman (1976, 1979) based on a binary choice, to a multinomial choice.

The article is organised as follows. Section 2 presents the theoretical household fuelwood demand model. Section 3 addresses the issues of econometric methodology, and notably the methods used to correct selection bias based on a polytomic choice model. Section 4 presents the database constructed on the basis of a survey conducted in 2006 by the BVA polling institute at the request of the Midi-Pyrénées Regional Energy Observatory (OREMIP). Finally, Section 5 is dedicated to the presentation and interpretation of the estimations produced by the econometric analysis of the data, before concluding in the final section.

## II. The theoretical model: household fuelwood demand

The specification of household fuelwood demand was based on the utility model, with $R^*$ the (stochastic) indirect utility function of the household, which we suppose to be unobserved. Indirect utility $V$ depends on the price of the resource $P$, income $Y$ and the socioeconomic characteristics of the household, noted $T$, and is defined conditionally on the choice of wood use category. We can therefore write:

$$R_{ij}^{*} = V_{ij}\left[P_j, Y_i, T_i\right] + v_{ij,}$$

where $j = 1,\ldots,J$ is the index of usage, $i = 1,\ldots,N$ that of the individuals and $v_{ij}$ the error term. The Roy's identity gives us the household's marshallian demand function for fuelwood:

$$X_{ij}\left(P_j, Y_i, Z_i\right) = \frac{\partial V_{ij}\left(P_j, Y_i, Z_i\right) / \partial P_j}{\partial V_{ij}\left(P_j, Y_i, Z_i\right) / \partial Y_i}.$$

When simplified, the fuelwood demand function conditional on category of use $j$ by household $i$ can be written as follows:

$$q_{ij} = \gamma_j z_{ij} + \eta_{ij}$$

where $q_{ij}$ is the quantity of fuelwood consumed by individual $i$ for usage $j$, $z_{ij}$ is a vector of the characteristics of the individuals (including the price of wood), $\gamma_j$ the vector of the related parameters and $\eta_{ij}$ the error term taking account of the influence of the unobserved variables.

## III. The econometric methodology

The available data raises a particular issue in that alongside those who do not use wood for heating (representing 54.8% of those surveyed in our sample), there are four different ways of combining wood with another energy:

1. Households use wood as the main source of energy for heating (16.4% of the total sample);
2. Households use electricity as the main source of energy for heating and wood as a back-up (8.4%);
3. Households use gas as the main source of energy for heating and wood as a back-up (8.9%);
4. Households use fuel oil as the main source of energy for heating and wood as a back-up (11.5%).

### *III.1- General description of the model*

The model to be estimated is a system composed of four demand equations (the fifth equation being excluded because it concerns households that consume no wood at all) and a selection criterion that determines whether the household is in one of the five categories. The switching simultaneous-equations model can be written as follows:

$$q_{ij} = \gamma_j z_{ij} + \eta_{ij} \quad \text{si } R_i = j, \quad j = 1,\dots,4, \tag{1}$$
$$R^*_{ij} = \beta_j x_i + \nu_{ij}, \tag{2}$$
$$R_i = j \text{ si } R^*_{ij} > \max_{j \neq j'}(R^*_{ij'}), \quad j = 1,\dots,4, \quad j' = 0,\dots,4. \tag{3}$$

Equation (1) represents the demand function for system $j$ defining the category of wood use for heating, with index $i$ representing the household. The selection criterion is modelled by equation (2), with latent variable $R^*_{ij}$ representing the indirect utility level of the household $i$ associated with category $j$, which will determine the choice of system. Equation (3) determines the mode of allocation between the different possible systems. $R_i$ is an observed variable indicating the choice made by the household $i$ according to its unobserved utility level.

To simplify the notations, index $i$ is now excluded. We define $\varepsilon_j = \max_{j \neq j'}(q^*_{j'} - q^*_j)$, equivalent to $\varepsilon_j < 0$. It is supposed that the error terms $\nu_j$ are i.i.d. according to a Gumbel law (Logit specification), the probability for household $i$ of choosing system $j$ is then written:

$$\Pr(\varepsilon_j < 0) = \frac{\exp(\beta_j x)}{\sum_{j=0}^{4} \exp(\beta_j x)}, \quad j = 0,\dots,4.$$

The first problem with this model is that it is based on a strong hypothesis referred to as IIA (*Independence of Irrelevant Alternative*). This means that the relationship between the two probabilities of belonging to a certain category (for example, the probabilities of belonging to categories 1 and 2) is independent of the other categories (for example, categories 3 and 4). Whether this hypothesis is true can be checked by a Hausman test. The second problem with the multinomial Logit is that it is impossible to identify parameter vectors $\beta_0$ to $\beta_4$ simultaneously. Because of this, the parameters relating to a given category are usually set to zero. The reference category we chose is that of non-consumers of wood, which is to say category 0. Consequently, vector $\beta_0$ is normalised to zero. The model is then rewritten:

$$\Pr(\varepsilon_j < 0) = \frac{\exp(\beta_j x)}{1 + \sum_{j=1}^{4} \exp(\beta_j x)}, \quad j = 1, \ldots, 4.$$

This model is estimated by the maximum likelihood method.

As written by Bourguignon et al (2007), the generalisation of the selection bias correction model is based on the conditional mean of $\eta_j$. We can posit $\Gamma = \{x\beta_0 + \cdots + x\beta_4\}$ and write:

$$E\left(\eta_j \middle| \varepsilon_j < 0, \Gamma\right) = \iint \frac{\eta_j f\left(\eta_j, \varepsilon_j \middle| \Gamma\right)}{P\left(\varepsilon_j < 0 \middle| \Gamma\right)} d\varepsilon_j d\eta_j = \lambda(\Gamma),$$

where $f\left(\eta_j, \varepsilon_j \middle| \Gamma\right)$ is the joint conditional density function of $\eta_j$ and $\varepsilon_j$. Given the fact that the relationship between the 5 components of $\Gamma$ and the 5 corresponding probabilities is reversible, there is a single function $\mu$ which can be substituted for $\lambda$ as follows:

$$E\left(\eta_j \middle| \varepsilon_j < 0, \Gamma\right) = \mu(P_0, \ldots, P_4).$$

The demand equation taking account of this correction is then written:

$$\begin{aligned} q_j &= \gamma_j z_j + E\left(\eta_j \middle| \varepsilon_j < 0, \Gamma\right) + u_j \\ &= \gamma_j z_j + \mu(P_0, \ldots, P_4) + u_j, \end{aligned}$$

where $u_j$ is an error term that is independent of the regressors.

From this general model, there are several approaches to correcting selection bias depending on more or less restrictive hypotheses: two parametric traditional approaches (Lee, 1983; Dubin and McFadden, 1984 or DMF) and one semi-parametric approach (Dahl, 2002).

As shown by Schmertmann (1994) and Bourguignon et al. (2007), the DMF method gives distinctly better results than those obtained using the method of Lee (1983). However, it remains sensitive to the restriction: $\sum_{j=0}^{4} r_j = 0.$ This constraint is removed by using the version proposed by Bourguignon et al. (2007). These authors also show that the correction proposed by DMF is more robust than semi-parametric correction proposed by Dahl (2002), "even when the selection term is highly non-linear". Finally, the selection bias in the equation of interest is suitably corrected with the DMF method, even when the IIA hypothesis is not confirmed in the choice model. Consequently, for our empirical analysis, we use the DMF method (Bourguignon et al. version). The DMF approach is described in the following sub-section, while the other approaches will be found in the annexes.

*III.2- Dubin and McFadden approach (1984) - DMF*

To construct the selection bias correction term, DMF made the following hypothesis based on the error term $\nu_j$ of the selection equation:

$$E\left(\eta_j \middle| \nu_0,\ldots,\nu_4\right) = \sigma\frac{\sqrt{6}}{\pi}\sum_{j=0,\ldots,4} r_j\left(\nu_j - E(\nu_j)\right),$$

where $\sigma^2$ is the variance of $\eta$ in the total sample and $r_j$ is the coefficient of correlation between $\eta$ and $\nu_j$. With the multinomial Logit model, we then write:

$$E\left(\nu_j - E\left(\nu_j\right) \middle| R_j^* > \max_{j'\neq j}(R_{j'}^*),\Gamma\right) = -\ln\left(P_j\right) = m\left(P_j\right),$$
$$E\left(\nu_{j'} - E\left(\nu_{j'}\right) \middle| R_j^* > \max_{j'\neq j}(R_{j'}^*),\Gamma\right) = \frac{P_{j'}\ln P_{j'}}{1-P_{j'}} = m\left(P_{j'}\right), \quad \forall\, j' \neq j.$$

In the original version of the model, Dubin and McFadden (1984) introduced the following restriction: $\sum_{j=0}^{4} r_j = 0.$ The equation of interest to be estimated can therefore be written:

$$q_j = \gamma_j z_j + \sigma\frac{\sqrt{6}}{\pi}\left[\sum_{j'\neq j} r_{j'}\left(m\left(P_{j'}\right) - m\left(P_j\right)\right)\right] + u_j\,.$$

Removing this constraint, the equation with correction of selection bias is therefore written:

$$q_j = \gamma_j z_j + \sigma\frac{\sqrt{6}}{\pi}\left[r_j m\left(P_j\right) + \sum_{j'\neq j}\left(r_{j'} m\left(P_{j'}\right)\right)\right] + u_j\,.$$

Once the multinomial Logit has been estimated and the correction terms constructed, we can then estimate parameters $\gamma_j$, $\sigma r_j$ et $\sigma r_{j'}$, then find $\sigma^2$, $r_j$ and $r_{j'}$. separately.

## IV. Descriptive analysis of the data

The data and certain important statistics in our study came from the "Survey of Household Energy Wood Consumption in the Midi-Pyrénées Region", carried out by the BVA polling institute and processed by the SOLAGRO association (2006).[5] For a more detailed descriptive analysis of this data, those interested may refer to it.

The questionnaire was in four parts. The first part collected information on the age and profession of the head of the household. The second was only for users of wood for heating, and concerned the category of fuelwood use (main, back-up or for pleasure) and the main characteristics of consumption. The third section was only for those who do not use wood, and addressed the reasons for their choice and the heating equipment available in the household. The last part concerned the whole sample and concerned the main heating energy of the household, the characteristics of the household and their dwelling and any recent changes in heating energy. In total, 2,254 interviews were conducted over the period 9 to 18 February 2006, with 1,019 long questionnaires (for fuelwood users) and 1,235 short questionnaires (for non-users of fuelwood). The survey covered the 2004-2005 heating season and the sample was representative of the Midi-Pyrénées region, with a statistical weight being allocated to each questionnaire to adjust the sample.

The calculation of the missing quantities of wood in the database was performed by SOLAGRO. The calculation was performed on the basis of a study of the discriminating variables enabling the quantity used to be described (type of use, supply method, specific equipment, date of construction of the dwelling, household head profession, wood purchased or not, etc.). The values were then allocated to the non-respondents by a Bayesian draw from among the people with the same characteristics.

A little over 50% of wood users declare that they do not pay for it. For them, the wood mainly comes from their own forest property and the rest from upkeep of their orchards, grounds, hedges etc. One solution would be to take these users out of the rest of the analysis, but this would pose a selection bias problem. We chose to keep these users in and to estimate a price of wood for them using a hedonic approach (see annexe).[6]

The average quantity of wood used came to 7.34 cubic metres. Consumption amounted to almost 12 cubic metres for households using wood as their main source of

[5] SOLAGRO is a not-for-profit association that conducts studies in the fields of energy, agriculture and the environment.

[6] Another solution to allocate a price would have been to use a "transport cost" type approach, with each household declaring its supply distance. One difficulty in implementing this method in the case at hand is that the supply distance variable is not very discriminating for users who declare that they do not pay for wood.

heating. It even exceeded 13 cubic metres for households using a wood boiler. When wood was used as a back-up source, consumption varied between 4 and 5 cubic metres, depending on the type of energy used as the main source.

For the Midi-Pyrénées region, the use of wood as the main energy source represented 1,639,684 cubic metres or 57.5% of total wood consumption. The remaining 42.5% were broken down as follows, with 12.5%, 13.2% and 16.8%, for electricity, gas or fuel oil respectively as the main source of heating energy.

The average price per cubic metre for the sample as a whole came to €41.91, representing an average annual budget of €307.62 per household for winter 2004-2005. It varied from about €38 per cubic metre for main use of fuelwood, to over €45 when wood was used as a back-up source for electric heating. Table I presents the descriptive statistics for the quantities of wood consumed and the different purchase prices. The annexes provide a summary of all the variables used, with their definition and the descriptive statistics that go with them.

**Table I**: *Descriptive statistics of price and quantity variables*

| **Variable** | **Definition** | **Mean** | **SD** |
|---|---|---|---|
| Q | Quantity of wood consumed by households (1019 obs.) | 7.34 | 6.46 |
| q1 | Quantity of wood consumed by households using it as their main source of heating (369 obs.) | 11.80 | 7.38 |
| q2 | Quantity of wood consumed by households using it as a back-up to electricity (190 obs.) | 4.86 | 3.80 |
| q3 | Quantity of wood consumed by households using it as a back-up to gas (201 obs.) | 4.42 | 4.13 |
| q4 | Quantity of wood consumed by households using it as a back-up to fuel oil (259 obs.) | 5.09 | 4.30 |
| Price | Purchase price of wood in Euros per cubic metre (1019 obs.) | 41.91 | 13.17 |
| Price1 | Purchase price of wood in Euros per cubic metre by households using it as their main source of heating (369 obs.) | 38.79 | 10.08 |
| Price2 | Purchase price of wood in Euros per cubic metre by households using it as a back-up to electricity (190 obs.) | 45.10 | 13.67 |
| Price3 | Purchase price of wood in Euros per cubic metre by households using it as a back-up to gas (201 obs.) | 44.88 | 15.76 |
| Price4 | Purchase price of wood in Euros per cubic metre by households using it as a back-up to fuel oil (259 obs.) | 41.70 | 13.45 |
| Pricem | Mean fuelwood price in the *département* (Euros per cubic metre). Source: *Observatoire Economique du Bois*. | 43.03 | 5.60 |

Note: non-weighted descriptive statistics.

The persons surveyed had to choose the monthly income bracket to which they belonged (under €750; from €750 to €1,000; from €1,000 to €1,500; from €1,500 to €3,000; and over €3,000). Despite the fact we were careful not to ask for precise monthly income, respondents were reluctant to divulge this information and there was a certain amount of missing data (376 observations). Specific processing was performed on the income variable (see the details in the annexes).

Between the professions and socio-professional categories (of the head of the household), energy wood use varied little on initial analysis. It can be noted, however, that wood was widely used by farmers, especially as the main source of energy (in second place, but a long way behind, came the merchants, trades and self-employed category), and was least used by employees and those without an activity (excluding retired people).

The following descriptive analysis is based on unadjusted data. It was observed that gas was the most widely-used energy as main source of heating (35.6%), followed by electricity (27.9%), fuel oil (20%) and wood (13.2%). Among the households in the sample, 45.2% used fuelwood as a source of heating energy, of whom 16.4% as the main source of heating. Fuelwood was often backed up by electricity when used as the main source of heat, and often appeared as a back-up (or for pleasure) with fuel oil (36.6%) and, to a lesser extent, for gas (30.7%). When households chose wood as the main source of heating energy, the back-up heating was most often powered by electricity (48%), with one-quarter of these households using no back-up heating, and fuel oil and gas coming in last place (18% in total).

About 62% of households had specific equipment for wood heating, such as a boiler, a room heater or an enclosed fireplace. Among users of wood, 39% used only an open fire. More than 85% of users of wood as the main source of heating used a wood-burning domestic appliance of the boiler type. More than one third of those using wood for pleasure or comfort were also equipped with domestic equipment of the stove type. More than four out of five of these appliances were the first to have been fitted, with the equipment renewal rate remaining slow for the moment.

## V. Analysis and interpretation of the estimation results

In this section, we will begin by analysing the results of the choice model (multinomial Logit), before turning our attention to our interest function (fuelwood demand). For the estimation of the discrete-continuous model, we used the STATA programme of Bourguignon et al. (2007). The estimation results were obtained with the DMF model (deemed to be the best by Schmertmann, 1994, and Bourguignon et al., 2007) in which the constraint on the parameters in terms of correction was removed. The results obtained with the models of Lee (1983) and Dahl (2002) are available on request from the authors.

*V.1- Estimation of the multinomial Logit choice model*

Our choice model was based essentially on the household and dwelling characteristic variables. As interpretation of the parameters of the variables in the multinomial Logit is not direct, for reasons of identification constraints (vector $\beta_0$ is normalised to zero), we will limit ourselves to a presentation of the variables that seem to have an influence on the choice and category of fuelwood use. The reference category that was chosen was non-consumption of wood. The estimated parameters therefore give the impact of the explanatory variable on the probability of choosing the category of use in relation to the reference category. However, the value of the coefficient cannot be interpreted directly, and we therefore calculated the marginal effects (for a mean value of the explanatory variables). We can also note that variables indicating the place of residence of the household were added to the regression to capture any specific effects there might be taking account of non-observed regional characteristics (such as forest cover, rural nature of the *département*, etc.). The different estimation results are presented in Table II.

**Table II:** *Multinomial Logit model estimation results.*

| | R=1 | | R=2 | | R=3 | | R=4 | |
|---|---|---|---|---|---|---|---|---|
| Variable | Estimated coeff. | Marginal effect | Estimated coeff. | Marginal effect | Estimated coeff. | Marginal effect | Estimated coeff. | Marginal effect |
| Constant | 10.2751 | | -12.3034 | | -15.0831 | | -9.9461 | |
| | *3.00164* | | *3.3929* | | *3.4310* | | *2.8636* | |
| Pricem | -0.1103 | -0.0017 | 0.0580 | 0.0021 | 0.0844 | 0.0023 | -0.0477 | -0.0023 |
| | *0.0679* | *0.0011* | *0.0726* | *0.0025* | *0.0742* | *0.0020* | *0.0605* | *0.0026* |
| Income | -0.0084 | -0.0001$^{***}$ | 0.0016 | 0.0000$^{*}$ | 0.0018 | 0.0000$^{**}$ | 0.0009 | 0 0000 |
| | *0.0006* | *0.0000* | *0.0007* | *0.0000* | *0.0007* | *0.0000* | *0.0006* | *0.0000* |
| Farmer | -1.3044 | -0.0127$^{***}$ | 1.3770 | 0.0738 | 1.6321 | 0.0765 | 1.0038 | 0.0514 |
| | *0.5761* | *0.0041* | *0.6452* | *0.0559* | *0.7572* | *0.0635* | *0.5631* | *0.0427* |
| Labourer | 0.7869 | 0.0159 | -0.2721 | -0.0101 | 0.5919 | 0.0190 | 0.1871 | 0.0074 |
| | *0.4309* | *0.0123* | *0.4349* | *0.0117* | *0.3994* | *0.0161* | *0.3836* | *0.0183* |
| Entrepren | 2.1928 | 0.0983$^{**}$ | -0.5997 | -0.0190$^{*}$ | 0.1076 | 0.0004 | 0.0453 | -0.0216 |
| | *0.5116* | *0.0502* | *0.5222* | *0.0104* | *0.5177* | *0.0130* | *0.4257* | *0.0168* |
| Exec | 5.0775 | 0.6094$^{***}$ | 0.0225 | -0.0223$^{**}$ | -0.2546 | -0.0194$^{***}$ | -0.0320 | -0.0294$^{**}$ |
| | *0.6314* | *0.1308* | *0.5317* | *0.0095* | *0.5306* | *0.0071* | *0.5251* | *0.0114* |
| Nbhouse | 0.7896 | 0.0119$^{***}$ | -0.0449 | -0.0022 | -0.0519 | -0.0018 | -0.0998 | 0.0040 |
| | *0.1201* | *0.0036* | *0.1181* | *0.0041* | *0.1201* | *0.0031* | *0.1065* | *0.0047* |
| Age | -0.0901 | -0.0014$^{***}$ | 0.0309 | 0.0001 | 0.0147 | 0.0004 | 0.0047 | 0.0002 |
| | *0.0114* | *0.0004* | *0.0116* | *0.0004* | *0.0121* | *0.0003* | *0.0103* | *0.0004* |
| Owner | 2.3948 | 0.0250$^{***}$ | 0.1114 | 0.0244 | -0.3547 | -0.0118 | 0.5959 | 0.0226 |
| | *0.3873* | *0.0074* | *0.4284* | *0.0143* | *0.4206* | *0.0133* | *0.3882* | *0.0139* |
| Declin | -0.4772 | -0.0059 | -0.3392 | -0.0100 | -0.2511 | -0.0053 | -0.4250 | -0.0160$^{*}$ |
| | *0.2882* | *0.0037* | *0.2588* | *0.0079* | *0.2660* | *0.0062* | *0.2455* | *0.0093* |
| D1948 | 0.1227 | 0.018 | -0.3823 | -0.0132 | 0.2792 | 0.0078 | 0.2433 | 0.0116 |
| | *0.2706* | *0.0042* | *0.29533* | *0.0090* | *0.2777* | *0.0083* | *0.2352* | *0.0116* |
| Dgas | -1.5489 | -0.0185$^{***}$ | -1.3376 | -0.0388$^{***}$ | 1.9552 | 0.0876$^{***}$ | -1.7974 | -0.0649$^{***}$ |
| | *0.3324* | *0.0059* | *0.2808* | *0.0107* | *0.2417* | *0.0230* | *0.3068* | *0.0149* |
| Apart | -4.8365 | -0.0341$^{***}$ | -0.8279 | -0.0201 | -2.5267 | -0.0365$^{***}$ | -1.2664 | -0.0374$^{**}$ |
| | *0.8396* | *0.0091* | *0.6058* | *0.0138* | *0.7740* | *0.0096* | *0.6713* | *0.0152* |
| T5 | 1.5429 | 0.0307$^{***}$ | 0.2519 | -0.0090 | -0.5309 | -0.0136$^{*}$ | -0.1340 | -0.0622 |
| | *0.2722* | *0.0100* | *0.2733* | *0.0089* | *0.2769* | *0.0069* | *0.2498* | *0.0104* |
| Equip1 | 6.9352 | 0.2371$^{***}$ | 5.7401 | 0.2503$^{***}$ | 5.4821 | 0.1530$^{***}$ | 5.1546 | 0.2096$^{***}$ |
| | *0.5813* | *0.0460* | *0 .5401* | *0.0443* | *0.5462* | *0.0353* | *0.4662* | *0.0389* |
| Equip2 | 4.5178 | 0.0759$^{***}$ | 5.0798 | 0.2863$^{***}$ | 4.7671 | 0.1637$^{***}$ | 4.7307 | 0.2750$^{***}$ |
| | *0.5836* | *0.0246* | *0.5351* | *0.0543* | *0.5355* | *0.0419* | *0.4633* | *0.0511* |
| Drecdwell | 0.5387 | 0.0078 | 0.9625 | 0.0390$^{***}$ | 0.7434 | 0.0205$^{*}$ | -0.0773 | -0.0670 |
| | *0.2759* | *0.0052* | *0 .2512* | *0.0144* | *0.2568* | *0.0098* | *0.2476* | *0.0101* |
| Alti | 0.4944 | 0.0068 | 0.0041 | 0.0041 | 0.1844 | 0.0036 | 0.6970 | 0.0301$^{**}$ |
| | *0.2875* | *0.0088* | *0.2844* | *0.0098* | *0.3033* | *0.0078* | *0.2519* | *0.0121* |
| # observations | | | 2254 | | | | | |
| Log-likelihood | | | -1451,75 | | | | | |
| LR Test $\chi^2_{80}$ (P-value) | | | 2950,44 (0,0000) | | | | | |
| Pseudo-$R^2$ | | | 0,504 | | | | | |

The reference category is that of non-users of wood
R=1 for wood as main energy
R=2 for electricity as main energy and wood as back-up
R=3 for gas as main energy and wood as back-up
R=4 for fuel oil as main energy and wood as back-up

The adjustment of the model to the data was satisfactory with a pseudo-$R^2$ of 0.5 and a chi-2 test that largely rejected the null hypothesis of all the parameters (p-value of 0.000). The model correctly predicted the category to which the households are allocated in over 75% of cases. The model correctly classified over 86% of the non-users of wood and 85% of the users of wood as the main source of heating. Model performance was lower for back-up use of wood, with correct prediction rates varying from 39% for combined use with gas to 62% with fuel oil. However, in 71% of cases, the model did predict back-up use of wood correctly.

Household income appears to be one of the most decisive variables in the choice of wood as the main source of energy. The estimated income coefficient for this use was significantly different from zero at a level of 1%, with the value of the marginal effect for the average individual being calculated to be -0.0001. These results can be interpreted as follows. A low income increases the probability of choosing wood as the main source of heating, rather than not using wood at all. More precisely, an average income that is €100 lower increases this probability by one point. As the probability of choosing wood as the main source of heating was estimated to be 4.4% (for the average individual), that means that this probability would increase to 5.4%. On the other hand, for uses of wood as a back-up source of energy, income had a significant effect but close to zero when wood was used in combination with electricity, but the sign was different compared with use of wood as the main energy. Consequently, the more household income increased, the more inclined they were to use wood as a back-up source of heating, rather than not at all. This time, an increase in income of €100 had the effect of not modifying the probability of choosing wood as the main source of heating. These initial results were consistent with the existing literature, such as Hosier and Dowd (1987) or Leach (1992). Wood used as main source of energy appears to be an *inferior good* while when it is used as a back-up, it has the characteristics of a *normal good*. These results will be confirmed by the analysis of wood demand.

The price of wood did not seem to have an effect on the probability of choosing wood as main or back-up source of energy. However, other factors did explain the probabilities of belonging to a given wood user category significantly and simultaneously. If the household owned its main residence, then this factor had a positive impact on the probability of using wood as the main source of heating (0.025). Also, if the household lived in an apartment rather than in a house, the probability of using wood decreased compared with consuming none. The marginal effect was stronger (in absolute value) for use as back-up heating. Also, if the dwelling had a mains gas connection, then unsurprisingly, the probability of using wood as a back-up source of heating for gas increased very significantly (with a marginal effect of 0.0876) while it dropped for all other categories of use.

If the head of the household belonged to the "executive" or "merchant, trades or self-employed" socio-professional categories, then the probability of using wood as main energy source increased. Conversely, the proportion of farmers using wood as the main energy was lower. If the household lived in a dwelling with more than five rooms, then the probability of using wood as the main energy was higher (0.031). For a dwelling with equipment for wood, the probability of consuming wood as the main or back-up source of heating increased, but this probability was even greater for an electricity/wood heating combination. The number of people making up the household only had a positive effect on the probability of using wood as the main heating energy.

*V.2- Estimation of demand equations*

In the first stage of our discrete-continuous model, we were able to find the choice probabilities and calculate the selection bias correction terms. These correction terms were then integrated into each demand equation, for wood used as the main heating energy and for wood combined with another source of energy (electricity, gas, fuel oil) used as the main heating energy. The consumptions for the four different usages of wood were noted respectively $q_1$, $q_2$, $q_3$ et $q_4$. As in all two-stage methods, the standard deviations of the second stage (with a least-squares estimation model) are biased. There are two ways to remedy this problem: either correct the standard deviations, as suggested by Heckman (1979) or Lee et al. (1983), or recalculate these standard deviations with a bootstrap method. It is the latter method that was used in the estimation programme of Bourguignon et al. (2007). The estimation results are shown in Table III.

**Table III:** *Demand equation estimation results*

| Variable | $\ln(q_1)$ | $\ln(q_2)$ | $\ln(q_3)$ | $\ln(q_4)$ |
|---|---|---|---|---|
| Ln(Price) | -0.4153*** | -0.1393 | -0.0487 | 0.0164 |
| | *0.1474* | *0.1538* | *0.1414* | *0.1915* |
| Ln(Income) | 0.0242 | -0.0967 | 0.3348 | -0.9849* |
| | *0.2086* | *0.5160* | *0.4876* | *0.4871* |
| Pleasure | | -0.5620*** | -0.2553* | -0.5005*** |
| | | *0.1275* | *0.1249* | *0.1209* |
| Entrepren | 0.2648* | | | |
| | *0.1425* | | | |
| Drecdwell | -0.2321* | -0.5323*** | | |
| | *0.1020* | *0.2028* | | |
| Dchang | | 0.3829* | | |
| | | *0.1701* | | |
| Nbhouse | | 0.1249* | -0.1176 | |
| | | *0.0608* | *0.0715* | |
| Equip2 | 0.3320** | | | |
| | *0.1415* | | | |
| Farmer | | | 0.7816** | |
| | | | *0.3171* | |
| Age | | | | -0.0118* |
| | | | | *0.0059* |
| Declin | | -0.2891 | | |
| | | *0.1890* | | |
| Alti | | 0.4231* | | 0.2723 |
| | | *0.2008* | | *0.1766* |
| Dgas | | | 1.2669* | 1.3376** |
| | | | *0.5614* | *0.5513* |
| Equip1 | | | | 0.2514 |
| | | | | *0.1589* |
| Constant | 3.6871** | 1.1285 | -2.4251 | 8.0963* |
| | *1.5148* | *4.4253* | *3.909* | *4.3503* |
| $m(P_0)$ | 0.94092* | 0.1806 | 0.1792 | -0.2092 |
| | *0.4504* | *0.6508* | *0.3539* | *0.4703* |
| $m(P_1)$ | -0.0647 | 0.0121 | -0.6550* | -0.0831 |
| | *0.1314* | *0.5163* | *0.3645* | *0.4961* |
| $m(P_2)$ | -1.0229* | -0.2889* | -0.1155 | -0.1729 |
| | *0.4802* | *0.1595* | *0.4222* | *0.3866* |
| $m(P_3)$ | 0.0031 | 0.2912 | -0.0301 | 1.4592* |
| | *0.4809* | *0.5078* | *0.0877* | *0.6571* |
| $m(P_4)$ | 0.3288 | 0.9581 | -1.5352*** | -0.1886 |
| | *0.5518* | *0.6455* | *0.3185* | *0.1041* |
| $\sigma^2$ | 1.0140** | 0.8068 | 6.8565*** | 2.5724* |
| | *0.4286* | *0.9393* | *2.2703* | *1.3973* |

Notes: the standard deviations (in italics) were calculated by a bootstrap method, with 500 replications for each demand equation.

Certain coefficients associated with a correction term $m(P_j),\ j = 0, \dots, 4$ were significantly different from zero (in particular for wood demand with main use of gas). There was therefore a selection bias. This result confirms the hypothesis according to which the estimation of separate demand equations, without taking account of the endogenous decision on the type of wood use, would have resulted in biased estimations.

Before commenting on the estimation results, it should be noted that the continuous variables (quantity, price and income) were log transformed beforehand. In this way, it was possible to interpret the coefficients associated with the price and income variables directly as elasticities.

First of all, very different fuelwood demand price elasticity levels were observed according to the category of wood use (main use or back-up with electricity, gas or fuel oil). Elasticity varied from -0.42 in the case of main wood use, to values that were not significantly different from zero in the case of back-up use. These differences mean that the estimation of a single demand function comprising the different types of wood use would have resulted in a specification error. The demand model estimated by OLS for all the households consuming fuelwood gave a significant price elasticity of -0.15, for example.

The use category that was most sensitive to price was use of wood as the main energy source (in the case of main use, the average bill was more than double that in the case of back-up use). Its price elasticity was significantly different from zero and negative, with a value equal to -0.42. A 10% increase in wood price therefore led to a drop in consumption by about 4.2%. Wood demand price elasticities for the three categories of use (electricity and wood, gas and wood, fuel oil and wood) were not significantly different from zero. These elasticity levels were close to the mean level (-0.10) found by Mackenzie and Weaver (1986) for the United States.

The signs of the coefficients associated with the income variable differed from the results of the energy choice model. The coefficient of the income variable was significantly different from zero only in the case of wood used as a back-up for fuel oil used as the main energy source. The impact of income on wood consumption seemed to be very small.

Other factors explain the variations in the quantities of wood consumed. In particular, wood consumption was quite obviously lower when wood was used just for pleasure and comfort (in a fireplace, for example). Finally, the socio-professional category had an influence on wood consumption. For example, farmers consumed more wood when their main heating was gas powered, showing the substitution effects that can exist in certain categories of the population to a slightly greater extent.

## VI. Simulations

In this section, we simulated a variation in fuelwood prices and analysed its impact on household energy choices and on their fuelwood consumption. The scenario in question was a drop of 10% in fuelwood prices, all other things being equal (and the prices of other energies, in particular). This scenario of a fall in price can in fact be interpreted as a comparative gain of 10% against the unit cost of other energies. The results are reported in Table IV.

**Table IV:** *Impact of a 10% fall in wood price on energy choices and fuelwood consumption*

| | **Observed data** | | | **Predictions (observed price)** | | | **Predictions (Δp=-10%)** | | |
|---|---|---|---|---|---|---|---|---|---|
| | **No of households (%)** | **q** | **Q (%)** | **No of households (%)** | **q** | **Q (%)** | **No of households (%)** | **q** | **Q (%)** |
| **No wood** | 1235 (54.8%) | - | - | 1193 (52 .9 %) | - | - | 1206 (53.5%) | - | - |
| **Wood main source** | 369 (16.4%) | 11.8 | 4355 (58.2%) | 416 (18.5%) | 10.1 | 4200.0 (63.2%) | 481 (21.3%) | 10.5 | 5034.3 (70.3%) |
| **Wood back-up + elect.** | 190 (8.4%) | 4.9 | 923 (12.3%) | 159 (7.0%) | 3.4 | 546.1 (8.2%) | 85 (3.8%) | 2.9 | 248.2 (3.5%) |
| **Wood back-up + gas** | 201 (8.9 %) | 4.4 | 888 (11.9%) | 214 (9.5%) | 3.5 | 751.1 (11.3%) | 168 (7.4%) | 3.6 | 604.0 (8.4%) |
| **Wood back-up + fuel oil** | 259 (11.5%) | 5.0 | 1318 (17.6%) | 272 (12.1%) | 4.2 | 1148.2 (17.3%) | 314 (14 .0%) | 4.0 | 1273.0 (17.8%) |
| **All use categories** | 2254 | 3.3 | 7485 | 2254 | 2.9 | 6645 | 2254 | 3.2 | 7159 |

Notes: q: Average individual wood consumption (in cubic metres). For example, the average consumption observed in households using wood as the main source of energy comes to 11.8 cubic metres.

Q: Total wood consumption (in cubic metres) of the sample. The percentage corresponds to the share of the category of use in question in consumption, calculated for the Midi-Pyrénées region. For example, the use of wood as the main energy source represents 58.2% of the volume consumed in Midi-Pyrénées.

First of all, it should be emphasised that the multinomial Logit resulted in a good representation of the different categories of users and non-users of fuelwood. The breakdown of households by category was in fact quite close between the observed data and that simulated with the observed price of wood. The wood demand models also worked quite well, although they did result, on average, in a slight underestimation of the consumption levels for all classes.

Looking at the individual consumption of households per type of use, we noted that the 10% fall in the price of wood had only a moderate impact. For wood used as the main energy source, for example, average annual consumption rose from 10.1 cubic metres to 10.5 cubic metres, representing an increase of 4.0%. However, over the sample as a whole, consumption increased by 7.7% from 6,645 to 7,159 cubic metres. This change in overall consumption in fact owed more to changes in the categories of fuelwood use than to a direct price effect. If we again consider those households for which wood is the main energy source, their number rose from 416 to 481, which is an increase of almost 16%. Of these 65 new households using wood when the price fell by 10%, 13 households did not consume fuelwood previously.

These results should be analysed in more detail, but do have important consequences in terms of formalising fuelwood demand and in terms of public policies. First of all, as aggregate variations in wood consumption are much more the result of a change in the type of use than of direct price effects, this validates our approach consisting in modelling these two types of decision jointly. Then, in terms of public policy recommendations, these results suggest that subsidies for households opting for fuelwood (grants for appliances, for example), which will in fact provide incentives to switch energy uses, are effective tools to develop fuelwood. In parallel with these measures on appliances, public decision-makers may implement policies affecting resource prices, such as through subsidies on wood purchases. Despite the level of price elasticity shown, our results demonstrate that such a measure will have significant effects on the use of wood as the main and back-up energy source.

## VII. Conclusion

With oil prices soaring and world oil resources scheduled to run out in the medium-term future, a viable energy system could be one that allows more space for renewable energies. This would mean the gradual introduction of an energy system that is less and less dependent on fossil fuels and turns increasingly to solar, wind or biomass energies.

In this study, we looked into one of the essential components of such an energy system, which is to say energy from wood and therefore from forests (the main source of wood for energy purposes). The forest plays an important role in the preservation of our ecosystem through carbon dioxide sequestration. Also, the combustion of wood in modern boiler plants contributes to reducing emissions of greenhouse gases into the atmosphere. The objective of this study was twofold: on the one hand, to make up for the almost-total lack of studies of domestic energy wood consumption in France and in developed countries in general and on the other hand, to highlight the factors that determine consumption and the type of energy wood use.

Our econometric study was based on the hypothesis of endogenous choice of the type of wood use (wood as the main source of heating or as a back-up for other energy sources – electricity, gas, fuel oil) which must be taken into account when estimating household demand to avoid selection bias problems. Our analysis showed that the choice of wood as the main source of heating energy was negatively linked to income, which would seem to confirm the energy ladder theory according to which wood is much more widely used by the poorest categories in society. It was also noted that it tended to be the highest-income households that used wood as a back-up source of heating energy or for pleasure. However, as our estimates show, income alone is not enough to explain the way in which wood is used. The price of wood, for example, can have a dissuasive effect in the choice of wood as the main source of heating energy. It also appears that certain household characteristics, such as the age of the head of the household, socio-professional category or the type of housing have a significant influence on their choice.

Wood consumption determinants, meanwhile, varied according to the way in which wood was used. For example, the quantity of wood consumed as the main source of heating energy was influenced by price, with a price-elasticity that was evaluated at -0.42, while wood consumption as a back-up source of heating did not vary significantly according to price. This is explained by the fact that the price of other energies is rising faster than that of wood, and that there would therefore seem to be substitution effects between wood on the one hand, and gas, fuel oil and electricity on the other.

This study could be taken further by taking account of prices and quantities of wood substitutes for heating and the characteristics of each type of energy. This would make it possible to make a detailed study of the problem of substitution between the different possible heating energies. However, this preliminary study does provide a better understanding of consumption of renewable energies, such as wood, and essential indications for implementing public economic and environmental policies.

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## Annexes

### A.1 Selection bias correction methods in polytomic choice models

*A.1.1- Lee approach (1983)*

The lee method (1983) is an extension of that of Heckman (1979) to the multinomial Logit. It is relatively simple to use and requires just one correction parameter to be estimated. However, it is obtained at the price of restrictive hypotheses (normality, linearity, etc.). The distribution function of $\varepsilon_j$ is noted $F_{\varepsilon_j}(.|\Gamma)$. $J_{\varepsilon_j}(.|\Gamma)$ is defined by the following transformation:

$$J_{\varepsilon_j}(.|\Gamma) = \Phi^{-1}\left(F_{\varepsilon_j}(.|\Gamma)\right),$$

where $\Phi$ is the distribution function of the standard normal law. The equation corrected for selection bias can therefore be written:

$$q_j = \gamma_j z_j - \sigma_j \rho_j \frac{\phi\left(J_{\varepsilon_j}(.|\Gamma)\right)}{F_{\varepsilon_j}(.|\Gamma)} + u_j,$$

where $\sigma_j^2$ is the variance in $\eta_j$ and $\rho_j$ the coefficient of correlation between $\varepsilon_j$ and $\eta_j$.

The estimation procedure is performed in two stages: first, the $\beta_j$ parameters of the multinomial Logit are estimated to construct the (predicted) correction term for each demand equation, and then the parameters $\gamma_j$ and $\sigma_j\rho_j$ of the demand equation by a least-squares method.

*A.1.2- Dahl approach (2002)*

Dahl (2002) proposed to restrict all the probabilities in $\mu(P_0,\ldots,P_4)$ and to choose a subset $S$ of all the possible categories (less one) which is particularly interesting in that it contains all the relevant information. This hypothesis can be written in the following form:

$$f\left(\eta_j, \varepsilon_j \middle| \Gamma\right) = f\left(\eta_j, \varepsilon_j \middle| P_{j,\, j\in S}\right).$$

The correction term of Dahl (2002) can therefore be written $\mu\left(P_{j,\, j\in S}\right)\cdot$ One particular case proposed by Dahl is to make the hypothesis that the probability of the alternative $j$ is the only information we need to estimate the equation of interest. This considerably reduces the number of parameters to be estimated in the equation corrected for selection bias. The corrected demand equation is therefore written:

$$q_j = \gamma_j z_j + \mu\left(P_j\right) + u_j.$$

## A.2 The variables

### *A.2.1- The Income variable*

À l’aide d’un modèle Logit ordonné, nous avons régressé le revenu sur plusieurs facteurs dont les professions et catégories socioprofessionnelles (PCS) qui expliquent en grande partie les variations de revenus. Cette estimation nous a permis de faire des prédictions de revenu pour les individus n’ayant pas répondu à cette question. On a pu ensuite calculer le revenu espéré pour tous les ménages.

**Table V:** *Results of the ordered Logit*

| Variables | | |
|---|---|---|
| Nbhouse | 0.4715 | *** |
| | *0.1124* | |
| Age | -0.0321 | *** |
| | *0.0118* | |
| T5 | 1.2790 | *** |
| | *0.2658* | |
| Surflog | -0.0762 | |
| | *0.0794* | |
| Owner | 1.5310 | *** |
| | *0.3178* | |
| Woodheat | -1.6619 | *** |
| | *0.3208* | |
| Inactive | -1.0761 | |
| | *0.7479* | |
| Exec | 4.0279 | *** |
| | *0.7826* | |
| Entrepren | 2.9919 | *** |
| | *0.9375* | |
| Employee | 2.5362 | *** |
| | *0.7247* | |
| Labourer | 2.0605 | *** |
| | *0.6643* | |
| Intermed | 4.0162 | *** |
| | *0.8241* | |
| Retired | 1.2875 | * |
| | *0.6466* | |
| Apart | 1.4389 | * |
| | *0.7107* | |
| House | 1.8152 | *** |
| | *0.6999* | |
| Constant | -3.9530 | *** |
| | *1.1518* | |
| # observations | 1882 | |
| Log-likelihood | -2342.53 | |
| LR test (P-value) | 886.40 (0.0000) | |
| Pseudo-$R^2$ | 0.1591 | |

### *A.2.2- The Price variable*

The price paid was regressed on a set of variables reflecting the cost of wood acquisition and supply. These variables were the altitude of the *département* or municipality, the origin of the wood (same municipality as the dwelling, less than 10km away, etc.), the form of supply (just collected, cut by the household or by a third party, etc.) and the source of the wood (hedge upkeep, recovery, waste, etc.). Most of these variables were significant and the R2 was 0.21.

The hedonic model was then applied to predict the price of the wood the users declare they do not pay for, with this calculated price being interpreted as the market value of the wood. The mean price calculated in this way came to €37.8 per cubic metre, compared with an average price of €41.9 paid by users who declare that they pay for their wood, with the difference being statistically different from zero. This result confirmed the intuition that the opportunity cost of wood for users who do not buy it is lower than the market price. Finally we constructed a mean price for each *département* (noted Pricem) for purchases of fuelwood, on the basis of individual observations. This indicator reflects an exogenous market price for use in the energy choice model.

**Table VI:** *Results of the hedonic model for wood price*

| Variables | |
|---|---|
| Origin: from another municipality less than 10km away | -3.4678 |
| | 2.2593 |
| Origin: from another municipality more than 10km away | -0.2831 |
| | 2.0068 |
| Origin: from your municipality | 2.5178 |
| | 2.4166 |
| Supply: Other | -0.6422 |
| | 21.6444 |
| Supply: You go and collect it | -13.4609 |
| | 15.1906 |
| Supply: You cut it yourself | -18.1598 |
| | 15.2109 |
| Supply: You have it delivered | -7.0476 |
| | 14.9822 |
| Supply: You pick it up | -4.8726 |
| | 17.5559 |
| Explo3: It is scrap wood (packaging, pallets, joinery…) | 3.0018 |
| | 6.2790 |
| Explo4: It is recovered (sawmill offcuts or other) | -6.8784 |
| | 4.4622 |
| Explo5: From park and garden maintenance | 0.1158 |
| | 7.1672 |
| Explo6: From hedge maintenance (including roadsides) | 4.9812 |
| | 5.4356 |
| Explo7: From orchard or vine maintenance | -3.4743 |
| | 7.7376 |
| Explo8: From wood harvest or forest | -0.9865 |
| | 1.5506 |
| Prove2: Other | 1.7396 |
| | 7.1346 |
| Prove3: From a farmer | 3.1979 |
| | 4.7445 |

| | | |
|---|---|---|
| Prove4: From a specialised firm, wood merchant or forest cooperative | 4.4009 | |
| | 4.5388 | |
| Prove5: From a supermarket or service station | 24.2557 | * |
| | 11.7040 | |
| Prove6: From the property of a member of your family or of a neighbour or friend | 6.6246 | |
| | 5.2329 | |
| Prove7: From your property | 2.7140 | |
| | 7.5742 | |
| Prove8: Directly from a private individual or a forest owner | 2.5181 | |
| | 4.6303 | |
| Altitude | -0.0166 | *** |
| | 0.0060 | |
| Share of forest in municipality | -3.3337 | |
| | 5.1350 | |
| Constant | 60.5851 | *** |
| | 15.8897 | |
| # observations | 494 | |
| F(30,463) | 4.05 | |
| P-value | 0.0000 | |
| R2 | 0.2081 | |

### *A.2.3- Descriptive statistics of the variables*

**Table A.1:** *Definition of the variables and descriptive statistics*

| **Variable** | **Definition** | **Mean** | **SD** |
|---|---|---|---|
| Income | Expected annual income of the household in Euros | 1806.5 | 464.32 |
| Age | Age of head of household | 52.5 | 16.06 |
| Nbhouse | Number of people in the household | 2.71 | 1.28 |
| Alti | Altitude of the municipality of residence (in metres) | 270.44 | 175.87 |
| Forcov | Forest cover | 0.14 | 0.15 |
| Dwellsurf | Dwelling floor area | 121.1 | 67.2 |
| | | | |
| Pleasure | Binary variable = 1 if the household consumes wood just for pleasure and comfort | 0.12 | 0.33 |
| Equip1 | Binary variable = 1 if the household has specific equipment (wood burner, room heater, closed fireplace) | 0.28 | 0 .45 |
| Equip2 | Binary variable = 1 if the household has an open fireplace | 0.25 | 0.43 |
| Supply | Binary variable = 1 if wood supply is difficult | 0.04 | 0.21 |
| Declin | Binary variable = 1 if the household thinks wood is a declining energy | 0.20 | 0.40 |
| Owner | Binary variable = 1 if the household owns its main residence | 0.75 | 0.44 |
| Apart | Binary variable = 1 if the household lives in an apartment | 0.18 | 0.38 |

| | | | |
|---|---|---|---|
| T5 | Binary variable = 1 if the dwelling has more than 5 rooms | 0.39 | 0.49 |
| D1948 | Binary variable = 1 if the dwelling was built before 1948 | 0.26 | 0.44 |
| Dgas | Binary variable = 1 if the dwelling has a mains gas connection | 0.32 | 0.47 |
| Dopin | Wood a renewable energy | 0.84 | 0.37 |
| Drecdwell | Recent dwelling (built after 1975) | 0.34 | 0.47 |
| Dchang | Change of main heating energy in last 15 years | 0.28 | 0.45 |
| Supply-dif | Wood supply difficult | 0.04 | 0.21 |
| | | | |
| Inactive | Other inactive | | |
| Retired | Retired | 0.34 | 0.47 |
| Farmer | Binary variable = 1 if household head socio-professional category is farmer | 0.04 | 0.20 |
| Labourer | Binary variable = 1 if household head socio-professional category is labourer | 0.18 | 0 .38 |
| Employee | Employee | 0.09 | 0.29 |
| Intermed | Intermediate professions | 0.05 | 0.22 |
| Exec | Manager, higher intellectual profession | 0.08 | 0.28 |
| Entrepren | Binary variable = 1 if household head socio-professional category is merchant, trades or self-employed | 0.05 | 0.22 |

Note: descriptive statistics not weighted.