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Generalized mixed estimation of a multinomial discrete-continuous choice model for electricity demand

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GENERALIZED MIXED ESTIMATION OF A MULTINOMIAL DISCRETE-CONTINUOUS CHOICE MODEL FOR ELECTRICITY DEMAND

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ABSTRACT

In this paper, we applied the generalized mixed estimation approach to the problem of estimating the Quebec residential electricity demand for space and water heating. A multinomial discrete-continuous choice model is used and estimated in two stages. The discrete choice is modelled as a multinomial probit model, while the continuous choice is estimated from a reduced form approach which corrects for the simultaneity biases. The results indicate that the GM estimator which combines prior and sample information dominates the classical ML estimator of the MNP models and hence, provides better prevision for electricity consumption. Evidence also shows that heating-system capital and operating costs, households characteristics, and energy prices have a significant impact on the choice of heating systems and electricity use. In particular, price substitution effects are well predicted.

Keywords: Generalized mixed estimator, residential electricity demand, multinomial probit, discrete-continuous choice.
JEL classification: C, C13; C51; D12; Q41

1. INTRODUCTION

Traditionally, studies on residential electricity demand have been concentrated on electricity consumption without considering the relationship between heating system and electricity use. The work by Dubin and Mcfadden (1984) is the pioneering study that has addressed this issue. The authors have suggested a two-steps continuous-discrete model that links the choice of heating technology (the discrete choice) and electricity consumption (the continuous decision). Their findings attracted more other researchers in this field [Dagsvik and *al* (1987), Dennerlein (1987), and Branch (1993), amongst others]. Bernard, Bolduc and Bélanger (BBB, 1996) applied this two-steps approach to estimate the residential electricity demand in Quebec, using data from the 1989 Hydro-Quebec survey. They modelled the discrete choice part of the framework as a Multinomial Probit (MNP) with first-order autoregressive (AR(1)) error term to capture the correlation between heating system choices. In turn, Nesbakken (2001) estimated the total energy consumption from Norwegian micro-data of 1990, using a full information maximum likelihood (FIML) approach which estimates the discrete and continuous parts of the model simultaneously. The discrete part of the model was formulated as a conditional logit model that assumes independence between heating equipment choices. However, as BBB suggested, the FMIL is computationally unfeasible under a structure where the choices are mutually dependent. Moreover, Nesbakken (2001) underscored that only one of the most important parameters of the model was found as significantly different when the model was estimated by the two-steps procedure. Thus, this single problem can be eliminated by using a more efficient estimation technique for the discrete choice part of the model like the MNP model with AR(1) error process which was used in the BBB paper. Indeed, the findings by BBB indicated that the MNP with an interdependent structure of choices was a better framework for estimating their Dataset than both the Multinomial Logit (MNL) and Nested Multinomial Logit (NMNL). The MNP has markedly improved the log-likelihood function, while the likelihood ratio test for comparing the MNP model to the MNL one clearly rejected the MNL.

The purpose of this paper is to extend the BBB discrete-continuous choice model by estimating the discrete choice part of this framework from the generalized mixed estimation (GME) approach suggested by Kalulumia and Bolduc (1997), in nonlinear situations. This empirical Bayesian approach combines the sample information and a prior density function derived from a previous knowledge on model parameters. Kalulumia and Bolduc have studied the statistical properties of the generalized mixed estimator. They have showed that it is more efficient than the sample mean, or the conventional maximum likelihood (ML) technique. As in BBB, the discrete choice of space and water heating systems is modelled as a MNP with AR(1) error structure which contains the conditional logit model, as a special case. While this is the first time the GME approach is utilized in a multinomial discrete choice framework, our anticipation is that it will improve over the previous estimation results by BBB and provide therefore, better prevision for electricity demand, as well as for price and income elasticities. The empirical application confirms our expectation as the GME results dominate those obtained from the classical ML estimation of the discrete-continuous choice model.

The second section of the paper deals with the definition of the economic and statistical models, while the empirical results are discussed in the third section. The paper ends with the concluding remark.

2. THE DISCRETE-CONTINUOUS CHOICE MODEL

2.1 The Economic Framework

For the sake of comparison between the sample mean and the GME, we use in this study the same model specification as in the paper by BBB. In general, when we deal with a discrete-continuous model for residential electricity demand, the discrete choice refers to the selection of the energy-using equipment and the continuous decision refers to the optimal quantity of electricity consumption restricted by the investment decision in the discrete choice model. For economic consistency between both choices (discrete and continuous), electricity demand is derived from the Roy's identity applied to the conditional indirect utility function providing the level of satisfaction related to each heating equipment. More specifically, BBB use the following indirect utility specification conditional on heating equipment j:

$$V_{jn} = V_{jn}(p_e, p_g, p_o, y-r_j, z_j, z_n), \quad j = 1,\ldots,J_n. \tag{2.1}$$

Here, V_{jn} denotes the unobserved utility associated with the space-water heating system j for individual n, p_e is the price of electricity, p_g the price of natural gas, p_o the price of fuel oil, $y-r_j$ is the income net of annualized cost of purchasing and operating heating system j, z_j is a vector of attributes for heating technology j, and z_n is a vector of socio-economic variables for household n. The household chooses among the following (nine) space and water heating systems: gas and gas, gas and electricity, dual energy[1]

[1]In order to deal with important changes in heating energy cost due to large shifts in the weather, some consumers in the Quebec province use dual energy sources: oil/electricity or wood/electricity. According to1991-1992 dual-energy tariffs, electricity is used for all purposes when the weather is above -15ºC at 3.2 ¢/kWh. If the weather decreases below -15ºC, another source (wood or oil) is used for heating

and oil, dual energy and electricity, oil and oil, oil and electricity, electricity and electricity, wood and electricity, wood-electricity and electricity (wood and electricity for space, and electricity for water).

The electricity demand conditional on the chosen heating system j, is determined by Roy's identity as follows:

$$X_{jn} = -\frac{dV_j/dp_e}{dV_j/dy}, \qquad J = 1,\ldots,J_n \tag{2.2}$$

which may be written in a following functional form:

$$X_{jn} = g_{jn}(p_e,p_g,p_o,y-r_j,d_j,s_n), \qquad j = 1,\ldots,J_n. \tag{2.3}$$

For computation simplicity, Equations (2.1) and (3.4) are assumed to be linear in all arguments. Ideally, the defined discrete-continuous model is supposed to be estimated by a FIML technique where the probability of the joint event (j, X_{jn}) is maximized. The corresponding joint density function can be computed as $P(j,X_{jn}).h(X_{jn})$, which is the product of conditional and marginal density function. As stated in the introduction, this procedure is computationally unfeasible when indirect utilities are correlated, as well as the joint error structure. Hence, Dubin and Mcfadden (1984) and BBB (1996) ignore the structural relationships relating parameters appearing in $P(j,X_{jn})$, the discrete choice, and those involving in $h(X_{jn})$, the continuous choice. This assumption allows for a separate estimation of the two parts of the discrete-continuous model using a two-stage procedure. The household chooses first his costless space-water heating system j, and then given j, he chooses the optimal quantity of electricity consumption X_{jn}. Thus, its total electricity demand is computed as a weighted average of X_{jn} by the choice probability $P(j|X_{jn})$ over all heating options :

$$X_n = \sum_{j=1}^{J_n} X_{jn}\, P(j|X_{jn}) \tag{2.4}$$

In addition to the above sample information, the GME approach developed by Kalulumia and Bolduc (1997), supposes that prior knowledge on coefficients in the utility function (2.1) are available and modelled as set of linear stochastic restrictions. In the current application, the prior information on the

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purpose and the price of electricity jumps to 11.7 ¢/kWh. The marginal price of electricity for a regular residential client is 5.2¢/kWh.

discrete-choice model coefficients is obtained from a previous estimation of the same model, using data from the 1984 Hydro-Quebec survey. This information provides a prior density function π which will be jointly estimated from the GME technique. Let us now describe in our econometric model.

2.2 The Econometric Model

It is well known that the estimation of MNP models is computationally very demanding when the set of choices involved is large. In particular, if there are more than four available alternatives, the evaluation of the multiple integrals that represent the choice probabilities cannot be carried out from existing numerical integration methods. In that case, modelers who want to rely on the maximum likelihood (ML) based approach require simulation methods to calculate the response probabilities. Number of choice probability simulators have been suggested in the literature (see Hajivassiliou,1993). Those exhibiting the best properties are the Stern (1992), the Geweke, Hajivassiliou and Keane (GHK), and the MNL kernel (McFadden, 1989) choice probability simulators. In terms of computation time, the MNL kernel simulator comes first, followed by the Stern one. However, in the Monte Carlo experiments performed by Hajivassiliou (1993) the GHK simulator obtained the best overall performance, closely followed by the Stern's one. In order to simplify the estimation of MNP models, Ben-Akiva and Bolduc (1991) and Bolduc (1992) extended the McFadden (1989) method by suggesting an hybrid MNP formulation that contains the MNL model as a special case. In this approach, model parameters are estimated using the method of maximum simulated likelihood (MSL), where the choice probabilities are replaced with smooth MNL kernel simulators. In their empirical application, Bolduc, Fortin and Gordon (1996) showed that the performance of the latter simulator compares well to the Geweke, Hajivassiliou and Keane simulation method.

Let us now describe this hybrid MNP model with AR(1) error process in the GME framework suggested by Kalulumia and Bolduc (1997). For a household $n, n = 1,...,N$ and an alternative $j,\ j = 1,...,J_n$ where J_n is the number of heating systems in the choice set $C = [1,...,J_n]$, this model can be formulated as

$$y_{in} = \begin{cases} 1 & if\ V_{in} \geq V_{jn} \text{ for } j = 1,...,J_n \\ 0 & \text{otherwise, and} \end{cases}$$

$$V_{in} = Z_{in}\beta + \xi_{in} = Z_{in}\beta + \sigma_i \rho + v_{in}, \tag{3.1}$$

where y_{in} denotes the observed choice, V_{in} is the conditional indirect utility of heating system i as perceived by household n, Z_{in} is a $(1\times m)$ vector of characteristics of both household n and heating technology i, β is a $(m\times 1)$ vector of unknown parameters, and ε_{in} is a random disturbance which is introduced to account for factors such as unobserved heterogeneity and measurement errors. The random disturbance ε_{in} is modelled as a mixture of a normally distributed error ξ_{in} and an i.i.d. Gumbel disturbance v_{in}, where σ_i denotes the standard deviation specific to each alternative. In vector form, the model can be written as:

$$V_n = Z_n\beta + \varepsilon_n = T\xi_n + v_n. \tag{3.2}$$

Here, T is a J_n-diagonal matrix which contains the standard deviation σ_i on the diagonal. V_n and ε_n are $(J_n\times 1)$ vectors and Z_n is a $(J_n\times m)$ matrix. It is also assumed that heating system choices are correlated due to the similarity of energy type used in different heating choices (e.g. oil/oil and oil/electricity or electricity/electricity). The simple way to include such a correlated structure in the model is to assume that the disturbance term ξ_{in} follows a generalized AR(1) process: $\xi_n = \rho W\xi + \zeta$ or $\xi = (I_{J_n} - \rho W)^{-1}\zeta$, where $\zeta \sim N(0, I_{J_n})$. The scalar ρ is the correlation coefficient $(-1<\rho<1)$ and W is a $(J_n\times J_n)$ contiguity matrix that relates the alternatives. The weights w_{ij} in W are the parsimonious parametric function describing the effect of each error on the others (for more details see Bolduc, 1992). Under the defined AR(1) error-structure, the MNP model (3.2) is written as:

$$V_n = Z_n\beta + TP^{-1}\zeta_n + v_n, \tag{3.3}$$

where $P = I_{J_n} - \rho W$. According to the rank conditions, it is well known that one can only estimate a scaled version of model (3.3) expressed in terms of utility differences with respect to the utility of a given alternative. The required scaling is obtained by setting to one, the variance of the first error term in the differenced model. Another way to deal with the rank conditions in the original model (3.3) is to set $\sigma_j = 0$ and $w_{ji} = 0$ for the reference alternative j (say the first one, j=1). We use the latter scaling approach in our application, where the reference alternative is electricity/electricity heating system. Hence, only $J = J_n - 1$ utility functions are estimated, where $j = 2,..,J_n$. The joint vector θ to be computed includes the following vectors: $\beta = (\beta_1,..,\beta_m)'$, $\sigma = (\sigma_2,...,\sigma_{J_n})'$, and the scalar ρ.

The model (3.3) conditional on ζ_n defines a standard MNL model. Thus, the conditional probability of choosing heating system i by household n is expressed as

$$\Lambda(i|\zeta_n) = Pr(V_{in} \geq \max_{\forall j\in C\, j\neq i} V_{jn}) = \frac{\exp(z_{in}\beta + M_i\zeta_n)}{\sum_{j\in C}\exp(Z_{jn}\beta + M_j\zeta_n)}, \tag{3.4}$$

where M_i denotes the row i of matrix $M = TP^{-1}$ in model (3.3). The unconditional probability of choosing alternative i by individual n is then given by:

$$P_n(i) = \underbrace{\int_{-\infty}^{+\infty} \cdots \int_{-\infty}^{+\infty}}_{J} \Lambda_n(i|z) n(z, I_J) dz, \tag{3.5}$$

which is approximated in the MSL method by the following MNL kernel simulator:

$$S_n(i) = \frac{1}{H} \sum_{h=1}^{H} ?(i|?_{nh}), \tag{3.6}$$

where H is the number of draws. The likelihood function associated with the defined MNP model is then

$$f(\delta) = \prod_{n=1}^{N} \prod_{i \in C} P_n(i)^{y_{in}}. \tag{3.7}$$

The MSL estimator $\tilde{\delta} = (\tilde{\beta}', \tilde{\sigma}', ?')'$ of the K-dimensional vector δ is obtained by maximizing the log-likelihood $\ln f(\delta)$ where the choice probabilities (3.5) are replaced by simulators in (3.6). If the vector $\sigma = 0$ and $? = 0$, the MNP model defined here reduces to a pure MNL framework which is also considered in this paper.

Suppose now that in addition to the above sample information, prior information about β is also available. It is assumed to arise from an unbiased estimator $r = \beta^* + ?$, $? \sim N(0,\Omega)$, of the $m \times 1$ parameter vector β^* of the statistical model in (3.1) based on a previous sample, where $?$ is the sampling error, Ω is an $m \times m$ p.d. matrix and where the true value of β^* may be different from that of β in the current sample. If $\beta \neq \beta^*$, then one can find a scale parameter μ_l such that each element β_l of β equals the corresponding element β_l^* of β^* times μ_l, i.e. $\beta_l = \mu_l \beta_l^*$, $l = 1, \ldots, m$. This is equivalently written in vector notation as: $\beta^* = R(\mu)\beta$, where $R(\mu)$ is an $m \times m$ diagonal matrix denoted by $R(\mu) = diag(1/\mu_l, \ldots, 1/\mu_m)$ and $\mu = (\mu_1, \ldots, \mu_m)'$ is a vector of unknown scale parameters. The difference between the true values of parameter vectors is given by: $\beta^* - \beta = R(\bar{\mu})\beta - \beta = [R(\bar{\mu}) - I]\beta$, which is a measure of prior information bias. After substituting in $\beta^* = R(\mu)\beta$, the sample value $\beta^* = r - ?$ of β^*, one obtains the following set of prior stochastic restrictions:

$$r = R(\mu)\beta + ?, \quad ? \sim N(0, \Omega), \tag{3.8}$$

where the rank of the unknown $R(\mu)$ design matrix is p $(p \leq m)$. The likelihood function associated with this prior information model is then

$$p(\beta, \mu | r) = (2\pi)^{-m/2} |\Omega|^{-1/2} \exp\{(-1/2)[r - R(\mu)]' \Omega^{-1} [r - R(\mu)]\}. \tag{3.9}$$

2.3 The Model Estimation

The GME approach suggested by Kalulumia and Bolduc (1997) estimate the joint model combining the sample information in (3.7) and the prior knowledge in (3.9), using the ML technique. Assuming that ε_n and v_n are mutually independent, the joint likelihood function combining both prior and sample information is given by $l^*(\delta,\mu) = f(\delta).p(\beta,\mu)$. Therefore, the GM estimator $\hat{\theta} = (\hat{\delta}',\hat{\mu}')'$ which is considered in this study, is obtained by maximizing over $\theta = (\delta',\mu')'$, the following log-likelihood function:

$$L(\theta) = \sum_{i=1}^{N}\sum_{i\in C} y_{in}\ln P_n(i) - (1/2)[r - R(\mu)\beta]'\Omega^{-1}[r - R(\mu)\beta], \tag{3.10}$$

where the constant terms are dropped. The first order conditions for this ML problem are given by

$$\partial L(\theta)/\partial\delta = \sum_{n=1}^{N}\sum_{i\in C} Z_{in}\,[y_{in} - P(i|C)] + \frac{\partial\ln p(\beta,\mu)}{\partial\delta}, \tag{3.11}$$

where $\partial\ln p(\beta,\mu)/\partial\delta = [(R(\mu)'\Omega^{-1}?)' \quad 0']'$ and

$$\partial L(\theta)/\partial\mu = -\frac{\partial\,\mathrm{vec}(R(\mu))'}{\partial\mu}(I_m \otimes \beta)\Omega^{-1}?. \tag{3.12}$$

Accordingly, the simulated log-likelihood is given by

$$\hat{L}(\theta) = \sum_{i=1}^{N}\sum_{i\in C} y_{in}\ln S_n(i) - (1/2)[r - R(\mu)]'\Omega^{-1}[r - R(\mu)], \tag{3.13}$$

and the simulated form of the first-order condition (3.11) is

$$\partial\hat{L}(\theta)/\partial\delta = \sum_{n=1}^{N}\sum_{i\in C}\frac{1}{S_n(i)}.\frac{1}{H}\sum_{h=1}^{H} ?\,(i|?_{nh})\,\frac{\partial\ln ?\,(i|?_{nh})}{\partial\delta}\,[y_{in} - S_n(i)] + \frac{\partial\ln p(\beta,\mu)}{\partial\delta}. \tag{3.14}$$

Kalulumia and Bolduc showed that the GME derived from the maximization of (3.10) will have a justification if the prior and sample information are not in conflict with each other. Moreover, as it can be expected from the previous formulation of the prior information in (3.8), the estimation of each individual scale coefficient μ_l, $l = 1,\ldots,m$, does not bring any additional information to the conventional ML estimator $\tilde{\delta}$ of δ which ignores the prior judgement. The GME is of interest only if the number of scale parameters to be estimated can be reduced to $p<m$ by constraining some of those scale coefficients to be equal. Overall, Kalulumia and Bolduc suggested a likelihood-ratio (LR) based test for assessing the compatibility between prior and sample information. The null hypothesis of compatibility is defined as $H_0\!:\mu\in\Re^p$ and tested against

the alternative $H_1: \mu \in \Re^m$. This LR test is given by $\lambda = -2[L(U) - L(C)] \sim \chi^2_{m-p}$, where *L(U)* and *L(C)* are the maximum log-likelihood values for the unconstrained (classical MLE) and constrained model (GME), respectively. The constrained log-likelihood is equivalent to $L(U) = \ln f(\tilde{\delta}) - (m/2)\ln(2\pi)$, where $\tilde{\delta}$ is the MLE of δ. Under H_0, the prior and sample information are in agreement and hence, the GME results cannot be rejected and will dominate the classical ML estimation. Therefore, the GME $\hat{\theta} = (\hat{\beta}', \hat{\mu}')'$ is obtained by maximizing the log-likelihood function (3.10), subject to $\mu \in \Re^p$.

As to the continuous part of the discrete-choice model, we use the specification suggested by BBB. The only exception is that, we only use the reduced form (RF) approach to estimate the electricity demand for space and water heating system. This approach includes the MNP choice probabilities estimated in the first stage, as variables in the electricity demand regression.

3. EMPIRICAL RESULTS

In this section, we are now applying the generalized mixed (GM) estimator for our defined MNP model to the problem of estimating the electricity demand for space and water heating purpose from the discrete-continuous framework. The performance of the GME method is compared to that of the MLE which ignores stochastic prior information, using both the asymptotic MSE criteria and the comparison of individual asymptotic standard errors (SE).

3.1 Data description

The data set involved in the empirical application was obtained from the five-year postal survey by Hydro-Quebec in 1989, as well as from both Gas Metropolain and Quebec Government databases[2]. It consists of a sample of 3090 households drawn from a large data set of 45,833 respondents to whom a questionnaire was mailed. The sample was selected to include only single family houses (detached, semi-detached or raw with separate outdoor entrance) that were built (68%) or converted to another space heating energy source (32%) during the 1986-1989 period of stable energy prices. A stable price period is considered to give an even chance for each heating options to be chosen. Information on each questionnaire includes the type of heating system selected, the stock of electric appliances, the house

[2]Data on gas consumption was provided by Gas Metropolitain while those on energy prices which enter into the operating costs of heating technologies come from the Quebec Government (see BBB for more details).

characteristics, the stock of electric appliances, the annual electricity consumption in Kwh, and a limited set of socio-economic indicators. Nine space and water heating systems were chosen. Out of the 3090 households, 80% rely on electricity for heating space while 96% use it for water heating purpose. Dual-energy space-heating users are mostly electric (7%) than oil one (2.4%). Oil (2.9%) is mostly used for water heating while natural gas (1.5%) is mainly a space heating energy-source. The gas distribution network is available only in urban areas. It is motly dominated by industrial users.

The variables included in the discrete-continuous model can be summarized into eleven distinct groups. A detailed definition of each group of variables follows: SET = the population density in different regions; HDD = the heating degree-days; DATCONV = the year of heating equipment conversion (1986-1989); DATCON = the house construction year (1920-1989); NBPERS = the number of persons per household; SURF = house size (square feet); AGE = age of the household head; Y = the household income ($); PIOP = annual operating cost of heating system ($); PICP = annual fixed cost of heating system ($); and PICPY = a variable capturing the interaction effect between income and annual fixed cost (annual fixed cost x income ($)). As prior information, we use the estimation results of a similar model based on a sample of 5010 households collected in the same way and from the same population, during the 1984 Hydro-Quebec survey. The available results are coefficient estimates and their associated variance-covariance matrix. In order to save space, Table 1 presents only the ML estimates and their respective SE for the MNP and MNL models. Below, we are now discussing the results of the two-stage estimation of the discrete-continuous model for electricity demand for heating ends.

3.2 Discrete Choice of Heating System

As earlier indicated, we use the same model specification as in BBB, where the Matrix W is defined to capture the correlation between the choice and use of oil and electricity for both space and water heating, as well as the relationship between the two system using wood for space heating. The only exception is that we estimate three different standard deviations (s) instead of one in BBB.

Table 3 summarizes the results for both the GME and the classical MLE of the MNL and MNP models. The variable included in both models are given in the first column. As earlier indicated, the 7th option (electricity/electricity) is chosen as the reference choice. This explains why the coefficients to its utility function do not appear. The parameters in the differenced utility equations are interpreted as the impact of explanatory variables on the probabilities of choosing heating systems relative to the reference choice of electric heaters only. Note also that in this model, it is possible to estimate the effects of a variable on each alternative. Hence, in the naming notation adopted here, a variable name index *i* indicates a specific effect on alternative *i*, while a double index *ij* suggests an effect identical for alternatives *i* and *j*. As shown in column 2, out of 47 scale coefficients only *p*=19 groups of μ are estimated. This means that 28 (*m*-*p*=47-19) equality restrictions are imposed on the μ_l' s for the MNL and 32 such constrains (*K*-*p*=51-19) for the MNP model. The MNL and GM MNL estimates are given in columns 3 and 5, respectively, while those for the MNP and GM MNP are presented in columns 7 and 9. The LR tests for assessing wether the prior information is in accordance with the sample evidence are as follows. For the GME of MNL (GMEMNL), ? ' 7.41 which compared to the 5% critical value $?^2_{(28,5\%)}$ ' 41.34 clearly indicates non-rejection of the GM specification suggested in this application. For the GME of MNP (GMEMNP), ? ' 39.23<$?^2_{(32,5\%)}$ ' 46.19 which indicates that we cannot reject the null hypothesis of compatibility and hence, the GM estimation results obtained from this MNP model are accepted.

Looking at the estimator statistical performance, the figures in the last three rows clearly indicate that the GM estimator dominates the classical ML one with respect to both the SE of individual coefficients and the MSE criterion (trace of the var-covariance matrix). In fact, for the MNL model almost all the figures in column 6 (GME) are smaller than those appearing in column 4 (MLE) and $trVar(\hat{d})$ ' 20.73<$trVar(\tilde{d})$ ' 45.71. The t-tests related to the GME of the MNL model show that most coefficients are significant at 5% and affect the probabilities of choosing heating systems. The variable DATCONV3 which was not significant in the pure MNL model becomes significant in the GME framework. The results for the MNP model with 50 draws show similar features. First of all, as indicated in the last panels of Table 2, the GME of the MNP dominates all the MSL results in the sense of both the MSE et the SE of individual parameters. Almost all numbers in column 10 (MSL) are greater than those in column 13 for the generalized mixed estimation, and $trVar(\hat{d})$ ' 100.4<$trVar(\tilde{d})$ ' 113.44. The t-tests in column 14 show that all variables are significant at 5% including the relevant variable SURF89 which was not important in explaining the probabilities of heating options 8 and 9 in the classical MNP results. Furthermore, the GME requires only a half of replications (*H*=25) needed in the MNP simulation. There is therefore a clear evidence that the GM estimator provides a more accurate prediction of the probabilities of choosing space-water heating systems. Since these estimated choice probabilities are used as variable in the continuous choice, the GME technique will also provide better prevision of the electricity consumption for space and water heating purpose.

However, we find as in BBB that the MNP model with stochastic interdependencies is consistent with the data. Both s and ? coefficients are significant at 5%. The LR test of choosing between the MNP with 50 draws and the MNL formulation indicates rejection of the MNL (*LR* ' 61.53>$?^2_{(4,5\%)}$ ' 9.49). The comparison between the GM MNP and the GM MNL from the LR test also leads to the rejection the GM

MNL (LR ' $22.36 > ?^2_{(4,5\%)}$). It is then clear that the MNP model with AR(1) error structure is the most appropriate framework for this application. As such, only the GME results for MNP model are discussed in more details and used as input in the continuous model estimation. Let us now first discuss the variable effects on alternative choices.

The constant term estimates exhibit a negative sign for all options. This is a clear indication of a preference for electricity energy source for space and water heating over all available options. The most important one is the electricity input in a heating system, the more likely is the system to be chosen. Among the 8 options, the least likely to be chosen are the gas/gas (-28.8) and oil/oil options (-18.1). In contrast, systems that have a fairly large electric space or water heating component increases the probability of being selected than the gas/gas or oil/oil option. This includes for instance, the wood-electricity/electricity option (-4.0), the wood-electricity choice (-5.9), and the gas/electricity (-6.2) and dual energy/electricity systems (-7.1). Overall, the constant estimates reveal that an increase of electricity input in a given heating system raises its probability to be bought. The population density (SECT) increases from rural to urban areas. The estimates related to the effects of this variable show that households living in higher density population areas are more likely to choose gas (1.999) than electricity (the reference choice). As previously indicated, the gas distribution utilities are concentrated in urban areas which explains the attractiveness of this option in high density-population regions. The estimates also indicate that the more urban is the area, the lower is the probability of choosing the wood option (-0.748). The effect of a colder climate (more heating degree-days, HDD) is an increase of the likelihood of choosing heating technologies which use gas, oil and wood than electricity. The result can be understood through the impact of house size (SURF). The coefficient estimates for systems 4, 5 and 6 are positive, while the effect is negative for systems 8 and 9. This suggests that the larger is the residence size, the higher is the probability of choosing the systems which rely on dual energy and oil for space heating, and the less likely is the wood option to be chosen (-0.130). The reason is that, despite their low capital costs, electric heating systems have relatively high operating costs associated with large space heating requirements. As such, households dwelling in larger detached houses are more inclined to choose heating systems that use oil or gas for space heating. On the other hand, the negative impact of house size on wood heating system is due to the fact that larger detached houses are mostly located in urban areas where this option is less attractive. In sum, colder weather (higher HDD) combined with lager house or space heating size decrease the utility of electric heating systems.

Furthermore, the results show that the older the household head (AGE) is, the higher the likelihood of choosing dual energy/electric heating option (4), and the less likely he is to select wood for space heating (alternatives 8 and 9). An explanation for this result is that the use of the latter system requires much physical efforts by users than the other types of energy. The findings also indicate that the higher the household income (Y), the more likely he is to choose a technology using both space and water heating. Moreover, the higher the annualized capital cost (PICP) and the operating cost (PIOP) of choosing a heating system, the lower the probability of selecting that system. The positive effect of income interacted with fixed costs (PICPY) indicates that richer households are more likely to choose more expansive heating systems.

2.3 Electricity Demand

From Roy's identity and (3.1), total electricity demand conditional on the choice of heating systems is given by the following linear equation (BBB):

$$X_{jn} = \sum_{i \in C} \gamma_i \phi_{ij} + \bar{P}'\beta_1 + z_n'\beta_2 + \alpha_1\Big(y - \sum_{i \in C} PIOP_i \phi_{ij}\Big) + \alpha_2\Big(\sum_{i \in C} PICP_i \phi_{ij}\Big) + \varepsilon_{jn}, \tag{4.1}$$

where X_{jn} is the annual electricity consumption in Kwh, $\bar{P}$ is a vector of energy prices (electricity, oil and gas), z_n is vector of both household and residence characteristics, and ε_{jn} is a random disturbance. In addition to the variables appearing in the choice model, the following household attributes are involved in (4.1): HOUSETYPE (1-detached, 2-semi-detached, 3- row of 3 or more), NROOM (number of rooms), OWNER (1= owner, 0=renter), and GASAVA (natural gas availability). Different effects of electricity price are computed for households who use electricity for space heating (PELSPACE) and water heating (PELWATER).

As indicated in section 2, we use only the reduced form (RF) method to estimate Equation (4.1). In this method, the ϕ_{ij} in (4.1) are replaced by the estimated MNP choice probability $S_n(i)$ computed from the GME technique in the first step (Dubin, 1985). The RF approach is free of estimation biases that can arise due to the simultaneity between heating system choice and electricity use.

Table 4 presents the RF estimation results. The first Panel provides the results when the choice probabilities replacing the ϕ_{ij}'s in (4.1) are computed from the classical MLE of MNP model as in BBB, while those in the second Panel make use of the $S_n(i)$ estimated from the GME technique. As anticipated, the model using the probabilities estimated from the GME approach performs better than that using the probabilities simulated from a pure MNP model. Indeed, the t-test values given in the last column indicate that relevant coefficients such as options 1, 2, and 5, as well as the electricity and oil prices, and SECT are now significant in predicting electricity demand. Furthermore, the first segment of Table 4 shows that the choice of gas (1 and 2), dual energy (3 and 4), oil (5 and 6) and wood (8) heating systems reduce significantly electricity consumption (all their effects are negative). An increase in electricity price lessens electricity consumption, while the effects of increased oil price or gas price is increased electricity demand (substitution effects). The higher the population density (SECT), the higher the electricity consumption. For households living in non-detached houses (HOUSETYPE), electricity consumption is lower. The more recent is the house construction date (DATACON) or the conversion date (DATACONV), the lower the electricity consumption. The estimates in the last two columns also indicate that electricity consumption increases with the size of the house (SURF), the number of persons (NBPERS), the number of rooms (NROOM), and the age of the household head (AGE). Another noticeable result is that house owners use less electricity than renters (OWNER). Electricity consumption appears to raise with household income (YNET).Thus, electricity behaves like a superior goods since higher income increases both the probability of choosing electric heating system and the use of electricity.

The short-run price and income elasticities of electricity demand were also computed. The results, which are not presented in this paper, indicated that both price and income elasticities were relatively low as evidenced in previous studies by BBB, Dubin and MacFadden (1984) and Neabakken (2001). They are available upon request. Overall, the GME method provides better predictions for both the choice probabilities of heating systems and electricity use.

4. CONCLUSION

In this study, we applied the generalized mixed (GM) estimation approach suggested by Kalulumia and Bolduc (1997) to the problem of estimating the Quebec residential electricity demand for space and water heating from a discrete-continuous choice framework. A MNP model which assume correlation between heating system choices were used as the discrete part of the model, while a linear model was assumed for the estimation of the electricity consumption in the second stage. The model was estimated in two steps because the computation of a simultaneous framework is almost unfeasible when the choices are interdependent as evidenced in the current application. The reduced form method, which is free of the simultaneity biases, was used to estimated the electricity demand. The results clearly indicate that the GM estimator which combines prior and sample information dominates the classical ML estimator of the MNP model and hence, it provides better prevision for electricity consumption. Indeed, relevant explanatory variables such as energy prices (electricity and oil), house size, and population densities become significant in explaining both the choice probabilities and the electricity consumption. None of the simultaneous biases mentioned by BBB were found in our estimation results (mainly the non significant coefficient to the price of electricity).

Finally, our findings improve over those by BBB and evidence the significant impact of heating-equipment capital and operating costs, households characteristics, and energy prices on the choice of heating systems and electricity consumption. In particular, substitution effects are now well predicted by the results. An increase in the price of oil or gas shifts away from the use of those sources towards electricity and vice-versa.

Table 1: Prior information from the 1984 sample estimation

Parameters		MNP MODEL		MNP MODEL	
		Estimates (r)	SE(r)	Estimates (r)	SE(r)
Gas/gas	(1)	-8267960	1.797680	-11.910074	2.796518
Gas/electricity	(2)	-3.088535	1.123079	-3.200600	1.206613
Dual energy/oil	(3)	-16.852293	1.166729	-17.906578	1.348011
Dual energy/electricity	(4)	-13.276907	0.709021	-14.295775	0.408339
Oil/oil	(5)	-6.602405	1.954823	-6.885588	3.720252
Oil/electricity	(6)	-3.226899	1.419837	-3.538395	1.426472
Wood/electricity	(8)	-4.837764	0.671495	-4.988068	0.699197
Wood-elec./electricity	(9)	-4.948458	0.720331	-5.072145	0.731778
SECT1		0.427273	0.115564	0.614446	0.173559
SECT23		0.130578	0.048043	0.143503	0.051341
SECT89		-0.062708	0.087760	-0.058957	0.093810
HDDM1		0.799878	0.279574	1.245504	0.420270
HDDM2		0.782520	0.220246	0.911045	0.233028
HDDM5		0.863009	0.256623	0.918592	0.556169
HDDM6		0.136446	0.265906	0.164469	0.253893
HDDM89		0.868050	0.103437	0.940889	0.109274
DATCONV1		0.173753	0.060812	0.168706	0.062753
DATCONV3		1.192571	0.086109	1.298565	0.099981
DATCONV4		1.032517	0.051952	1.125477	0.027747
DATCONV5		-0.037166	0.084367	-0.020862	0.094364
DATCONV6		0.085274	0.027737	0.112921	0.025572
DATCONV9		0.005572	0.019786	0.009256	0.019967
DATCON12		-0.215695	0.034009	-0.278131	0.052389
DATCON3		0.139242	0.027684	0.138831	0.033969
DATCON5		-0.105359	0.094883	-0.120336	0.105228
DATCON89		-0.063261	0.013330	-0.093182	0.014698
NBPERS1		0.136813	0.089813	0.209683	0.136741
NBPERS2		-0.179484	0.106699	-0.177232	0.105791
NBPERS3		0.174803	0.047239	0.161492	0.049700
NBPERS5		0.282026	0.102865	0.276197	0.130489
NBPERS6		-0.096261	0.109467	-0.102239	0.102274
NBPERS8		0.186702	0.045369	0.207042	0.049130
SURF4		0.149138	0.062076	0.170876	0.070450
SURF56		0.182020	0.164283	0.204720	0.175425
SURF89		0.288604	0.083917	0.336615	0.090868
AGE1		0.115653	0.076652	0.181163	0.106842
AGE4		0.097401	0.025882	0.098506	0.029172
AGE89		-0.263667	0.039703	-0.272339	0.044233
Y2		-0.332906	0.086779	-0.423370	0.089341
Y3		-0.434899	0.064142	-0.544794	0.073517
Y4		-0.296365	0.042489	-0.366256	0.047768
Y56		-0.639938	0.086800	-0.744752	0.087735
Y8		-0.693400	0.057414	-0.747076	0.054510

Y9	-0.641940	0.080025	-0.718190	0.085366
PIOP	-2.079388	0.811233	-1.681957	0.909785
PICP	-2.889704	0.301870	-3.369533	0.312797
PICPY	1.079368	0.089761	1.270001	0.094666

Table 2: GM and ML estimation results for the heating-system choice model

Model specification		MNL		GMEMNL		MNP		GMEMNP	
Parameters	Groups	Estimates	t-tests	Estimates	t-tests	Estimates	t-tests	Estimates	t-tests
Gas/gas (1)	1	-16.571	-3.789	-16.001	-5.516	-28.216	-3.593	-28.814	-3.465
Gas/electricity (2)	2	-8.038	-2.293	-8.083	-4.540	-6.114	-1.358	-6.187	-2.010
Dual energy/oil (3)	3	-5.769	-5.908	-5.668	-9.554	-5.771	-3.232	-7.098	-5.478
Dual energy/elec. (4)	3	-5.306	-7.630	-4.463	-9.602	-5.129	-4.858	-7.728	-198.11
Oil/oil (5)	2	-16.823	-7.225	-16.609	-7.939	-18.126	-5.402	-18.143	-5.545
Oil/electricity (6)	4	-9.686	-5.166	-9.669	-5.743	-10.044	-5.953	-10.135	-7.089
Wood/electricity (8)	5	-2.957	-3.347	-2.650	-7.625	-8.741	-4.488	-5.882	-10.059
Wood-elec./elec. (9)	3	-1.709	-1.886	-1.732	-6.187	-6.571	-3.486	-3.955	-5.764
SECT1	9	0.716	3.205	0.709	4.685	1.169	2.602	1.199	2.495
SECT23	1	0.273	2.715	0.289	4.278	0.285	1.743	0.383	1.439
SECT89	12	-0.5209	-5.177	-0.526	-5.553	-0.979	-5.514	-0.748	-6.250
HDDM1	2	2.215	2.752	2.088	3.919	3.914	2.925	3.701	1.904
HDDM2	1	1.492	2.125	1.533	4.306	1.327	1.566	1.412	2.323
HDDM5	2	2.173	6.733	2.174	7.441	2.489	5.870	2.588	5.792
HDDM6	13	1.408	4.428	1.438	4.914	1.627	5.358	1.634	5.755
HDDM89	5	0.396	3.036	0.460	8.270	1.374	4.512	1.046	11.093
DATCONV1	8	0.193	1.941	0.194	3.870	0.408	2.283	0.392	2.794
DATCONV3	5	0.631	7.429	0.620	11.951	0.739	3.755	0.746	5.410
DATCONV4	5	0.518	10.282	0.542	13.382	0.581	7.419	0.927	56.77
DATCONV5	14	0.468	3.881	0.466	4.059	0.591	3.370	0.491	2.898
DATCONV6	4	0.257	3.541	0.264	4.488	0.325	4.384	0.335	4.608
DATCONV9	15	0.081	1.806	0.088	2.357	0.042	0.920	0.020	0.385
DATCON12	8	-0.268	-3.724	-0.253	-6.973	-0.345	-3.486	-0.373	-2.784
DATCON3	5	0.064	0.920	0.073	4.673	0.099	0.629	0.102	0.769
DATCON5	10	0.136	1.125	0.136	1.186	0.171	0.944	0.109	4.569
DATCON89	6	-0.046	-1.573	-0.051	-4.841	-0.169	-3.114	-0.095	-1.369
NBPERS1	19	-0.435	-2.415	-0.445	-2.640	-0.662	-2.136	-0.750	-1.581
NBPERS2	8	-0.176	-0.778	-0.201	-1.919	-0.414	-1.409	-0.325	-1.621
NBPERS3	4	0.548	4.642	0.616	7.175	0.704	3.260	0.921	5.761
NBPERS5	4	0.888	4.592	0.892	5.243	1.101	4.600	1.170	5.148
NBPERS6	17	0.366	2.144	0.366	2.183	0.481	2.440	0.517	3.236
NBPERS8	16	-0.364	-4.743	-0.408	-6.039	-0.415	-4.126	-0.564	-9.131
SURF4	2	0.399	2.574	0.327	3.060	0.517	2.309	0.686	3.667

SURF56	4	0.517	2.031	0.528	2.315	0.673	2.293	0.690	2.272
SURF89	18	-0.151	-1.335	-0.147	-1.419	0.272	1.224	-0.130	-2.925
AGE1	4	0.339	2.263	0.353	2.781	0.328	1.058	0.447	1.018
AGE4	7	0.331	4.669	0.226	4.775	0.342	2.848	0.356	4.396
AGE89	1	-0.448	-6.640	-0.486	-10.458	-0.835	-6.297	-0.664	-8.185

Table 2. (Continued)

Model specification		**MNL**		**GMEMNL**		**MNP**		**GMEMNP**	
Parameters	Groups	Estimates	t-tests	Estimates	t-tests	Estimates	t-tests	Estimates	t-tests
Y2	1	-0.605	-3.585	-0.625	-5.214	-0.842	-5.088	-1.043	-4.806
Y3	9	-0.593	-4.925	-0.661	-7.399	-0.849	-4.768	-0.911	-7.229
Y4	9	-0.438	-5.014	-0.480	-7.346	-0.649	-4.562	-0.646	-4.131
Y56	6	-0.451	-3.992	-0.503	-7.535	-0.611	-4.463	-0.71	-6.062
Y8	8	-0.759	-11.272	-0.785	-14.298	-1.198	-12.069	-1.083	-15.28
Y9	6	-0.485	-6.329	-0.500	-9.360	-0.888	-7.727	-0.802	-7.664
PIOP	11	-9.757	-21.941	-9.527	-23.127	-13.486	-18.788	-13.176	-24.87
PICP	8	-2.821	-5.894	-3.166	-10.346	-4.332	-5.908	-4.694	-12.579
PICPY	6	0.816	7.858	0.861	11.160	1.155	6.965	1.302	8.477
SIG1						0.956	2.472	1.029	1.99
SIG2						0.001	0	0.037	0.357
SIG3						1.363	4.104	0.548	2.013
RHO1						0.763	12.389	0.816	8.515
MU01				1.922	9.265			2.511	4.897
MU02				2.505	7.602			3.586	4.331
MU03				0.335	9.448			0.552	75.691
MU04				3.294	5.345			3.750	11.723
MU05				0.524	12.155			0.832	249.215
MU06				0.819	10.740			1.114	16.501
MU07				2.231	3.209			6.364	2.453
MU08				1.143	11.993			1.525	37.885
MU09				1.636	6.775			1.933	9.196
MU10				-1.284	-0.868			-0.732	-4.875
MU11				4.354	2.939			2.891	41.270
MU12				10.924	0.561			20.806	1.230
MU13				16.995	0.702			13.659	2.239
MU14				-12.729	-0.809			-14.921	-0.689
MU15				17.109	0.268			0.929	1.899
MU16				-2.087	-3.425			-11.036	-3.035
MU17				-3.690	-0.843			-4.967	-1.469
MU18				-0.516	-1.287			-0.360	-10.236

MU19				-3.393	-1.287			-11.127	-0.192
Model LR-tests		1981.607		2045.141		2557.15		1816.445	
Trace of $Var(\hat{d})$		45.709		20.733		113.435		100.439	
Log-likelihood		1592.451		1639.346		1561.684		1628.165	

Notes: *The 5% critical value of the t-statistic is: 1.96. The $?^2$ critical values for the LR-tests are respectively, $?_{(47,5\%)}$ ' 64 for MNL, $?_{(66,5\%)}$ ' 85.97 for GMEMNL, $?_{(51,5\%)}$ ' 68.67 for MNP, and $?_{(70,5\%)}$ ' 90.53 for GMEMNP.

Table 3: Estimation Results for the Electricity Demand Model

Parameters	REDUCED FORM With MLE of MNP Choice Probabilities		REDUCED FORM With GME of MNP Choice Probabilities	
	Estimates	t-tests	Estimates	Estimates
Constant (7)	15320.5	1.38	1345.12	1.71
Sn(1)	-7260.39	-1.94	-6501.43	-3.45
Sn(2)	-1648.32	-0.1	-1350.63	-2.87
Sn(3)	-7763.22	-2.54	-7012.32	-3.11
Sn(4)	-9746.17	-3.67	-8567.23	-5.61
Sn(5)	17450.45	1.76	-1456.12	-2.31
Sn(6)	-55284.86	-2.64	-4989.89	-2.89
Sn(8)	-9068.57	-3.7	-8312.56	-3.5
Sn(9)	16633.07	1.55	-15976.16	-1.95
Electricity price	-33111.14	-1.75	-30872.02	-2.76
PELSPACE	191874.78	8.34	191897.89	1.73
PELWATER	12445.71	2.22	105500.91	1.43
Oil price	29404.22	0.12	27345.23	3.12
Gas price	124123.12	2.7	11541.12	2.74
SECT	262.41	1.73	261.34	2.66
HOUSETYPE	-523.78	-7.61	-545.01	-7.45
DATCONV	-348.23	-2.51	-350.25	-2.61
DATCON	-723.12	-7.32	-710.25	-8.71
NROOM	738.87	6.12	616.2	5.23
NBPERS	1435.12	8.17	1501.01	9.2
SURF	3.12	9.71	2.89	7.62
OWNER	-1520.17	-3.09	-1242.17	-4.51
AGE	70.23	4.67	60.02	3.23
YNET(weighted)	0.06	4.34	0.04	3.3
PICP(weighted)	2.8	3.2	3.02	4.01
GASAVA	-150.61	-0.7	-167.67	-1.05
$\bar{R}^2$	0.341		0.35	

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