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Dipartimento Economia e Statistica Cognetti de Martiis

Working Paper Series

21/17

SWITCHING BEHAVIOR AND THE LIBERALIZATION OF THE ITALIAN ELECTRICITY RETAIL MARKET. LOGISTIC AND MIXED EFFECT BAYESIAN ESTIMATIONS OF CONSUMER CHOICE

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Switching behavior and the liberalization of the Italian electricity retail market. Logistic and mixed effect Bayesian estimations of consumer choice

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Abstract

The paper assesses the effects of the liberalization of the Italian electricity retail market by providing the first account of the determinants of switching by Italian households. It covers the interplay between demand and supply by including market concentration and horizontal integration among the factors that drive the choice of consumers. Finally, it inaugurates the application of Bayesian estimations in this topic area and presents a new dataset.

1 Introduction

Ten years after the liberalization of the retail electricity markets in the EU, there is no widespread consensus on the benefits achieved (Concettini and Créti, 2013). The paper assesses the functioning of the Italian market by focusing on switching behavior.

Among the many indicators suggested by the EU (CEER, 2015, p. 9), switching behavior is currently under the spotlight of the European institutions. The completion of liberalization has given consumers a chance to "shop around" and, indirectly, it has invested them with responsibility for feeding competitive pressure. Indeed, active consumers can switch to better contractual conditions thereby forcing retailers to provide better services at cheaper fares. Moreover, switching rates also measure the participation of consumers in the market and, given the approaching energy transition, their likelihood to adopt smart technologies.

The analysis of switching is made complex by the interplay of economic and non-economic elements; and it is further complicated by the features of the exchanged good. On the demand side, electricity is a necessary good, but its cost has little impact on a typical household's income, and switching results in limited savings. Additionally, inactive behavior has no consequence for provision: households receive electricity through default obligatory electricity supplier schemes. On the supply side, the established monopolies have induced consumers' loyalty through long-term relationships generating inertia. Since liberalization, competitors face other critical issues: first, price competition has little scope since the largest part of the price of energy consists of taxes and transmission costs. Second, electricity is an undifferentiated good, and competition among retailers takes place mainly through innovation in services that are ancillary to electricity provision. The subsequent multiplication of offers may result in more difficult comparisons and in firms' opportunistic behavior (Grubb, 2015).

Our analysis grasps the complexity of switching behavior through examination of individual, household, and market variables. In line with the extant literature (see Table 1 and Section 2), we estimate the switching probability by using a logistic regression model in function of both household and individual variables. Moreover, in order to preserve household heterogeneity and to avoid arbitrary aggregation of individual variables, we extend the model by including random effects to cluster members of the same family. Problems with Newton-Raphson convergence (Albert and Anderson, 1984; Altman et al., 2003), caused by the high number of levels in the random component, are overcome by using a Bayesian parametric mixed Logit model (MLM) with a Markov Chain Monte Carlo (MCMC) method and a Gibbs sampler algorithm (Casella and George, 1992).

Analyses are conducted on data released by the Italian National Institute of Statistics in the survey on the Aspects of Daily Life (ADL). Data comprise demographic, geographic, attitudinal and psychological information on a representative sample of the Italian population. In addition to numerosity, such data have several useful characteristics. Since information is collected for general purposes, the data do not suffer from a framing effect. Moreover, the survey is carried out via paper questionnaires, thereby avoiding the self-selection generated by the use of web surveys. The latter are effective, fast and cheap ways to obtain data. However, when the accessibility of information is a variable under study, their use should be carefully assessed. Finally, the interaction between demand and supply is modeled through the introduction of an index of market concentration (CR3, i.e. the sum of the market shares of the three largest firms on the relevant market) derived from data published by the Italian Regulatory Authority for Electricity Gas and Water (AEEGSI).

The main findings concern the importance of joint switching, i.e. both electricity and gas. On the supply side, they show that horizontally integrated firms gain an advantage by proposing joint switching and by exploiting spillovers from joint marketing campaigns. On the demand side, they show that consumers learn from search activity and apply the same decision routine to different services. Secondly, the results suggest that information performs a dual role. An increasing amount of service-specific information (tariffs, provision, billing) reduces the probability of switching. This only apparently contradicts the assumption that more information leads to more active behavior. The discussion on the structure of the Italian electricity retail market will reveal that, under certain circumstances, non-switching is indeed the best available option. Instead, access to general information (via the Internet) increases the probability of switching. On the Web, besides service information, the consumer can find information loosely related to the service (e.g. political events, impending reforms in the sector) and that can alter the perception of the performance of the current retailer or contract. For instance, it has been shown that arousing fears concerning climate change has a positive effect on the intention to switch to green energy (Hartmann et al., 2016). Similarly Buryk et al. (2015) find that environmentally aware individuals are more willing to switch to dynamic tariffs when environmental benefits are disclosed. Moreover, the Internet exposes consumers to unwanted advertisements that might activate switching intentions. Finally, in more concentrated regional markets, switching rates are lower.

The paper is structured as follows: Section 2 reviews the literature on the topic. Section 3, describes the data and the Italian retail electricity market. The logistic regression model and its Bayesian mixed effect extension are presented in Section 4 and implemented in Section 5. Section 6 discusses and concludes.

2 Literature review

Switching behavior has been intensively studied from a marketing perspective (Keaveney, 1995; Peng and Wang, 2006) and in connection with utility markets liberalization. In both cases, the focus has been on the determinants of the switching decision. Although there is widespread agreement on the determinants of switching, there is no definitive evidence on their relative weights (see Table 1). The price of electricity and the associated savings are considered decisive factors in switching decisions. However, savings from switching are often very small (Sirin and Gonul, 2016) compared with the income of the average household. Consequently, incentives to undertake costly searches are low[1] (Giulietti et al., 2014; Klemperer, 1995; Wieringa and Verhoef, 2007). Moreover, empirical studies show that households exhibit a considerable degree of unresponsiveness to price changes (Daglish, 2016). In addition, doubts have been cast on individual rationality. Wilson and Waddams Price (2010) find that a sample of consumers who declared that they had switched solely for price reasons were nevertheless unable to fully appropriate the available gains (see also Annala et al., 2013). Besides price, switching is also affected by individual features and attitudes (e.g. demographic and psychological variables such as loyalty and trust) and service features (e.g. quality, failures, response to failures). Rowlands et al. (2004), in their study on the "kinds" and motivations of individuals more likely to switch electricity supplier, found that education and income have a positive effect on switching, whereas age has a negative one. Other studies find a negative effect of good relationship management (Yang, 2014; Wieringa and Verhoef, 2007) and of loyalty (Daglish, 2016). The quality and quantity of information about the service is considered a positive factor encouraging switching: a higher amount of information is commonly associated with more active and more efficient consumers (Gärling et al., 2008; Hortaçsu et al., 2015) and vice-versa (He and Reiner, 2015). Switching rates are usually modeled as resulting from the combination of several determinants. For instance, Gamble et al. (2009) jointly analyse the effect of loyalty to the incumbent, information search costs and expected economic benefits. Our analysis considers the observed switching rates as dependent on individual, household and market variables. Specifically, we use demographic (age, sex), social (education), geographical (location and municipality size), economic (adequate economic resources), and attitudinal (frequent Internet user) factors to characterize consumers. As regards their knowledge of the service, we focus on the satisfaction with the available information on it. The structure of the market is introduced via a measure of market concentration. The proposed analysis encompasses several models recognized by the literature and extends them by introducing novel variables such as the use of Internet and CR3. Due to the lack of data we do not account for the price of electricity; however, as we will discuss in Section 3, our results are consistent with the observed price dynamics.

Table 1: Selected literature

Title	**Question**	**Country**	**Data**	**Observations**	**Analysis**	**Findings** + : positive effect – : negative effect = : neutral effect
Consumer behaviour in restructured electricity markets (Rowlands et al., 2004)	"Kinds" of consumers who are likely to switch electricity supplier and their motivations	Ontario (Canada)	Survey data	315 and 601	Differences in means	Age (–) Education (+) Income (+)
Understanding customer switching behavior in a liberalizing service market: An exploratory study (Wieringa and Verhoef, 2007)	Determinants of customer switching	The Netherlands	Survey data Customer database data	7268	Principal Component Analysis Logistic regression Logistic regression with heterogeneity	Low relationship quality (+) Switching costs (–) Switching attractiveness (+) Heavy user (–) More contracts (–)
Customer switching behavior in service industries: An exploratory study (Keaveney, 1995)	Determinants of customer switching	Not specified	Interview	526	Descriptive	Price (+) Service failures (+) Competition (+) Ethical problems (+) Involuntary switching (+)
Consumer governance in electricity markets (Daglish, 2016)	Differences in switching rate before and after information campaigns and promotion of transparency in switching process	New Zealand	Meter data	1897085 (individual meter/month)	Conditional logistic regression	Loyalty (-) A certain degree of price changes (=) Information about retailer management (=)
Understanding household switching behavior in the retail electricity market (Yang, 2014)	Switching barriers	Denmark	Online data	1022	Logistic regression Principal Component Analysis Latent Class Analysis	Good relationship management (+) Price (+)
Behavioral aspects of regulation: A discussion on switching and demand response in Turkish electricity market (Sirin and Gonul, 2016)	Switching determinants	Turkey	Survey data	113	Multiple Correspondence Analysis panel data	Price (+) Low expected gains (-) Satisfaction (-) Risk/potential costs (-) Transaction costs (-)

3 The Italian retail electricity market

3.1 Data

The analysis of the Italian retail electricity market is performed on the Aspects of Daily Life survey (ADL). ADL is part of an integrated system of social analyses, the Multipurpose Survey on Households, carried out by the Italian National Institute of Statistics (ISTAT) and included in the National Statistics Programme. The ADL survey integrates objective and subjective dimensions of citizens' lives. On the one hand, it focuses on socio-demographic and living conditions, habits and household behaviours. On the other, it tries to capture individual opinions and expectations on social national services (including electricity). In more detail, ADL investigates the relationship between citizens and service providers, household switching choices, and individual opinions about electricity services and the quality of the information provided.

The analysis is based on data from ADL 2014, the latest released survey, carried out in the first months of 2014 and mainly referring to 2013. This survey covers a representative sample of Italian families composed of 44984 individuals belonging to 18864 households. Due to the anonymisation of the microdata file for research (Mfr), our final dataset with complete information is composed by 43567 individuals and 18448 households. In the estimations, we consider exclusively individuals of working age or retired, reducing the sample to 37217 observations. Information about the variables of the final dataset and some descriptive statistics are reported in Table 2.

3.2 Stylized facts

In accordance with the EU energy directives[2], Italy started electricity-market liberalization in 1999 (Dlgs 79/99), with the progressive unbundling of its national vertically-integrated monopoly (Enel) and the consequent development of competitive wholesale

Table 2: Descriptive statistics

Individual variables	N	%	Household variables	N	%	Electricity variables	N	%
Sex			*Number of members*			*Satisfaction with services provided*		
Male	21115	48.47	1	5613	30.43	Very satisfied	3087	16.75
Female	22452	51.53	2	5257	28.5	Quite satisfied	13100	71.09
Age			3	3654	19.81	Unsatisfied	1798	9.76
Not in working age(<16)	6350	14.58	4	3000	16.26	Very unsatisfied	443	2.4
In working age(16-64)	27253	62.55	5+	924	5.01	*Satisfaction with bill comprehensibility*		
Retired(>64)	9964	22.87	*Size of municipality*			Very satisfied	2102	11.46
Education (over 16)			Metropolitan area	3788	20.53	Quite satisfied	9216	50.22
University	4657	12.51	More than 10000 inhab.	8227	44.6	Unsatisfied	5198	28.33
High school	13314	35.78	Less than 10000 inhab.	6433	34.87	Very unsatisfied	1834	9.99
Secondary school	11452	30.77	*Geographical area (NUTS1)*			*Satisfaction with information provided*		
Primary school	6334	17.02	North-Western Italy	4156	22.53	Very satisfied	1838	10.07
No education	1460	3.92	North-Eastern Italy	4002	21.69	Quite satisfied	9242	50.66
Employment status (over 16)			Central Italy	3282	17.79	Unsatisfied	5299	29.05
Employed	15158	40.73	Southern Italy	5104	27.67	Very unsatisfied	1865	10.22
Jobseeker	4448	11.95	Insular Italy	1904	10.32	*Knowledge of switching possibility*		
Housewife	5432	14.59	*Economic resources*			Yes	15616	84.65
Student	2727	7.33	Excellent	161	0.87	No	2832	15.35
Retired	8358	22.46	Good	9831	53.29	*Supplier switch*		
Other	1094	2.94	Insufficient	7216	39.12	Electricity	1404	7.61
Use of the Internet (over 16)			Absolutely insufficient	1240	6.72	Gas	391	2.12
Frequent	19185	51.55				Electricity and gas	1376	7.46
Occasional	18032	48.45				None	15277	82.81

and retail markets. The process was completed with the deregulation of the retail market for domestic consumers, inaugurated on the 1st July 2007 and subject to temporary regulation until the 1st January 2018 (Ddl S.2085[3]). Under temporary regulation, domestic consumers may opt for a supplier on the free market or for a national electricity contract regulated by AEEGSI, the so-called "maggior tutela", where electricity is often supplied by the local distributor system operator (DSO). Tariffs depend on the fluctuations in the wholesale markets and are updated quarterly by the energy regulator agency. Customers that do no take action are assigned to the regulated service which, in 2013, still included 71.2% of domestic consumers.

This figure seems to testify to a difficult take-off of the Italian free market. The first issue to address in order to understand this datum is consumer awareness, defined as knowledge of their opportunities and of the rights and tools that can empower them to participate in the retail market (e.g. to switch product or supplier, to install a self-generation facility or similar, or even not to engage in some cases) (CEER, 2015, p. 9). In the dataset almost 85% of households are aware of their possibility to switch[4] but switching activity remains relatively low (see Table 2).[5] The switching rates reported in Table 2 in fact refer to cumulative switches over seven years.[6] Moreover, the figures also include switches from the free to the regulated market, which obviously do not bear witness to a satisfactory functioning of the former. The return to the regulated market, in fact, is quite high. According to AEEGSI (2014), in 2013 for every 7 households that had chosen the free market on average 1 had returned to the regulated market. Inertia is not caused by (perceived) informational difficulties, since Italian consumers are well informed and believe that they possess good information on the relevant aspects of the service (see Table 2, Electricity variables). To be noted is that individuals who have switched are less satisfied with the service provided than those who have not switched (see Figure 1). It follows that the answer to the question concerning the reason why aware and informed consumers do not engage in active behavior resides in the supply side of the market. A well-functioning retail energy market is characterised by several active suppliers and low market concentration within the relevant market. The Italian retail market satisfies the first condition, since the number of operators has been in constant expansion since 2007.[7] Instead, market concentration is definitely high. In 2013, the main operator controlled about half of market sales, and the first three operators (CR3) delivered 72.4% of energy volumes (AEEGSI, 2015).[8] As a confirmation of the imperfect functioning of the competitive forces, domestic households that have opted for the free market pay a price higher than they would pay on the regulated market with an increase that varies from 15% to 20% (with reference to procurement cost only). This is in line with the findings of studies which report that households remain largely unaffected by liberalization or even face higher power rates (Joskow, 2000; Steiner, 2004; Concettini and Créti, 2013; Ghazvini et al., 2016; Defeuilley, 2009).[9] Higher energy prices cannot be explained solely by the provision of ancillary services, since there is no conclusive evidence on the diffusion of new services especially for domestic customers (Fehr and Hansen, 2010). In Italy, for 2013, the official comparison tool (TrovaOfferte) reported only 30 offers. The figure is exceedingly low if compared with the number of active operators in the sector.[10] It follows that installation of smart metering and reading devices, which in Italy in 2013 had a roll-out coverage of 95%, has not generated the expected expansion in households services (Concettini and Créti, 2013). These critical issues are further complicated by the uneven geographical distribution of the observed variables. Discussion of the differences between northern and southern Italy would fall outside the scope of this paper. However, Figures 2, 3, and 4 show quite differentiated scenarios on the issue of interest, suggesting that caution is necessary when making general claims.

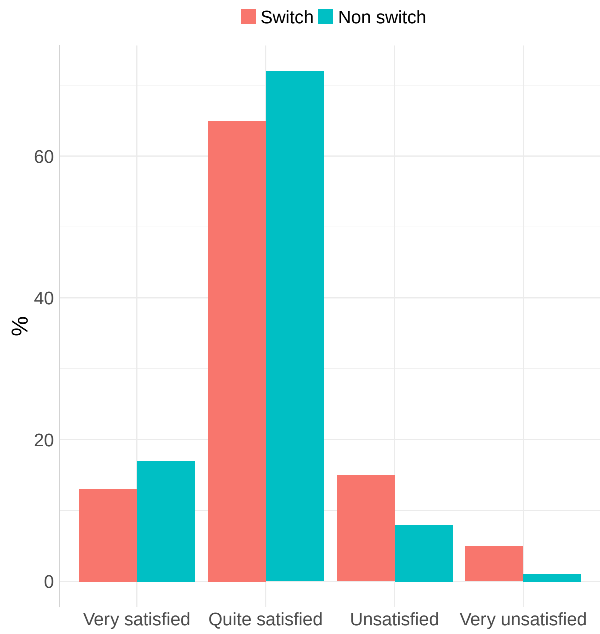
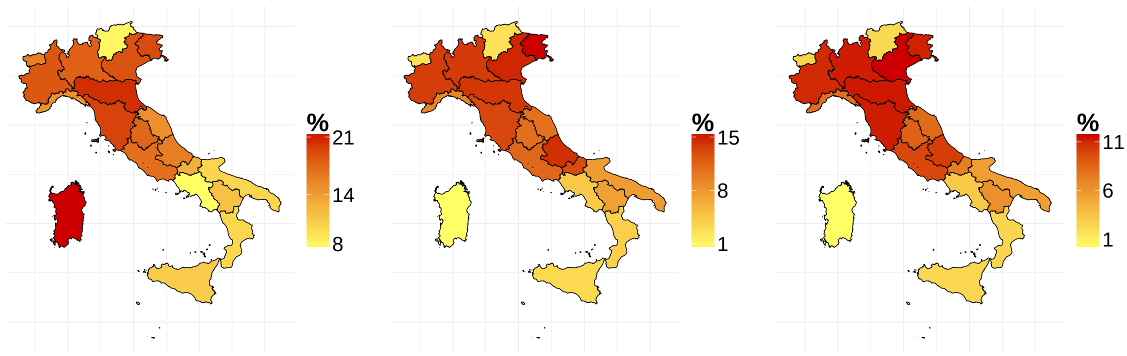


Figure 1: Satisfaction with provided electricity services

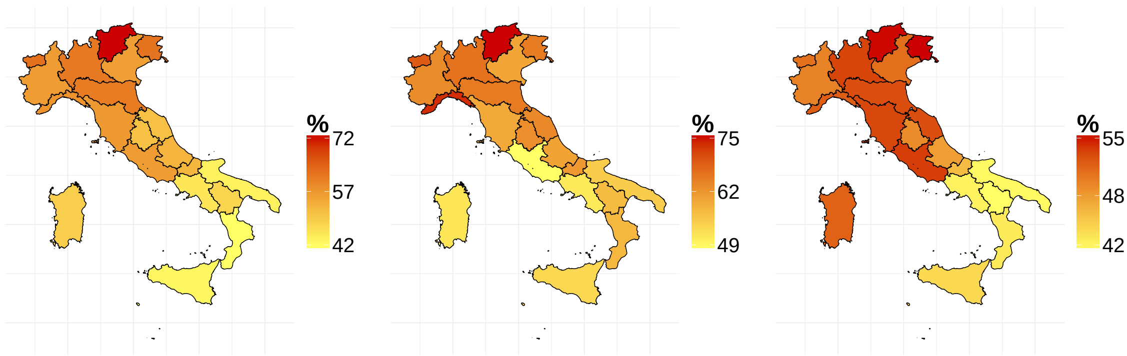


(a) Electricity switching rate
[7.16% - 21.57%]

(b) Gas switching rate
[0.27% - 15.62%]

(c) Joint electricity and gas switching rate
[0.13% - 11.60%]

Figure 2: Electricity and/or gas switching rates at the regional (NUTS2) level.



(a) Good economic resources
[41.49% - 72.57%]

(b) Satisfaction on provided information
[48.23% - 75.30%]

(c) Frequent use of the Internet
[41.18% - 55.41%]

Figure 3: Economic resources, information quality and quantity variables at the regional (NUTS2) level.

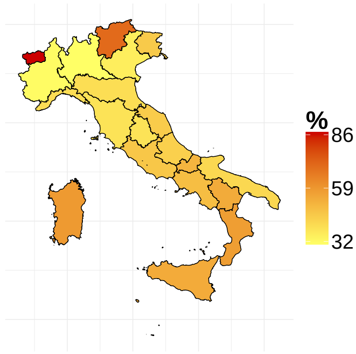


Figure 4: Retail market concentration at regional (NUTS2) level. [31.4% - 86.5%]

4 Methodology

The chosen econometric approach must allow the joint analysis of individual and household decision making. For this purpose, we adopted a discrete choice approach. The i^{th} decision maker's choice, $\forall\, i = 1, \ldots, n$, is between two possibilities: switch (S) and non switch (NS). The final option depends on the maximization of the decision maker's utility as described in the random utility models (RUMs) first introduced by Marschak (1960). We represent the decision of consumer i as the choice of j among a choice set $\mathcal{C}$ composed of the two alternatives: $j \in \mathcal{C}$ with $\mathcal{C} = \{S, NS\}$. We can easily represent a response variable Y_i as a binary random variable where $Y_i = 1$ if the decision maker switches and $Y_i = 0$ if s/he does not switch, i.e. $j \in \{0, 1\}$. By selecting the alternative $Y_i = j$, the decision maker i will obtain a utility U_{ij} modeled with a systematic (observed), V_{ij}, and a stochastic (unobserved), ε_{ij}, component, i.e. $U_{ij} = V_{ij} + \varepsilon_{ij}$. Therefore, the decision maker i will select the alternative $Y_i = 1$ if and only if $U_{i1} > U_{i0}$, where U_{i0} is the utility associated with the non switch option. Assuming that the stochastic components are independent and identically distributed (i.i.d.) $\varepsilon_{ij} \overset{iid}{\sim} \mathsf{Gumbel}(0, 1)$, we define a close form for the choice probability model widely known as the Logit model (McFadden, 1974; Luce and Suppes, 1965). Further assuming that the systematic component of the utility is linear in model parameters, i.e. $V_{ij} = \mathbf{x}'_{ij}\boldsymbol{\beta}$, the switching probability, under the aforementioned assumptions, reduces to

$$\pi_i = \mathsf{P}(Y_i = 1|X_i = \mathbf{x}_{i1}) = \frac{e^{\mathbf{x}'_{i1}\boldsymbol{\beta}}}{1 + e^{\mathbf{x}'_{i1}\boldsymbol{\beta}}} \tag{1}$$

where $\mathbf{x}_{i1}$ represents the $p \times 1$ vector of observed explanatory variables (for individual i and choice $j = 1$) and $\boldsymbol{\beta}$ is a $p \times 1$ vector of fixed effects (here with $p-1$ covariates and an intercept). For ease of exposition, we do not report the $j \in \{0, 1\}$ alternative indicator in the rest of the discussion.

The selection of this type of model makes it possible to work with a RUM and to take advantage of the representation of systematic taste variation, of the implications of a proportional substitution across alternatives, and of the possibility to capture the dynamics of repeated choice (if not correlated over time) (Train, 2003).[11]

The available data contain both household and individual information. This imposes the choice of the level of analysis (Goldstein, 2011). In order to preserve the maximum information detail and to avoid the loss of predictive power caused by the introduction of an arbitrary aggregation of individual information, we use individual level data and we extend the proposed model to account for household heterogeneity. We add random cluster and/or subject effects to account for the correlation of members in the same family. Therefore, we propose the more general version of the mixed Logit model (MLM), i.e. with fixed and random effects. The MLM is first introduced and applied as the hedonic demand model in Cardell and Dunbar (1980) and Boyd and Mellman (1980). However, only at the end of the last century, it becomes popular in theoretical and applied economics to mostly model transport demands (Bolduc and Ben-AkiWand, 1996; Brownstone and Train, 1998).

We introduce household heterogeneity by defining household `id` as the grouping variable to cluster errors in a mixed model. Formally: let Y_{kr} be the response variable of individual r in household k for $r = 1, \ldots, R_k$ with R_k the number of members of household k,

$k = 1, \dots, K$. Moreover, $\mathbf{x}_{kr}$ represents the vector of the values of explanatory variables, for fixed effect model parameters $\boldsymbol{\beta}$. In our case, we assume only a random intercept, i.e a univariate random effect u_k following Goldstein (2011) and Carota et al. (2017). Therefore, u_k is common to all R_k household members, i.e. $V_{kr} = \mathbf{x}'_{kr}\boldsymbol{\beta} + u_k$. Thus

$$\pi_{kr} = \frac{e^{\mathbf{x}'_{kr}\boldsymbol{\beta}+u_k}}{1 + e^{\mathbf{x}'_{kr}\boldsymbol{\beta}+u_k}}.$$

The proposed mixed Logit model is a flexible model that approximates any RUM (McFadden and Train, 2000) and overcomes the main limitations of a standard Logit model[12] for the description of individual choices.

Even if in a logistic regression model there are no local maxima[13] (Amemiya, 1985), it might still happen that the likelihood function has no maximum. This often results in a complete or quasi complete separation (Albert and Anderson, 1984; Altman et al., 2003; Lesaffre and Albert, 1989) implying that the maximum likelihood estimate does not exist. In other words, this occurs when $\mathsf{P}(Y_{kr} = j | X_{kr} = \mathbf{x}_{kr})$ is nearly perfectly predicted by a predictor or a linear combination of predictors (Webb et al., 2004). Therefore, the introduction of a random effect based on the household `id` (especially with a high number of levels, as in our case) could result in a non convergence of the Newton-Raphson method (Cox, 1970) used to solve for $\boldsymbol{\beta}$ the associated nonlinear system of equations. The problem, that is not solved by increasing the number of iterations, can be overcome by adopting a parametric (Kahn and Raftery, 1996) or semi-parametric (Hsu and Leonard, 1997) Bayesian approach (Allison, 2008; Altman et al., 2003; Lesaffre and Albert, 1989). Moreover, the possibility to reinterpret the logistic regression model in a Bayesian fashion has also some significant advantages, especially in the presence of random effects. Firstly, a Bayesian MLM increases the flexibility and the computational tractability of the classic MLM[14], even if it does not allow a formal distinction to be drawn between fixed and random effects since each effect is endowed with a suitable prior distribution.[15] Secondly, consistency and efficiency of estimators can be attained under milder conditions.

In general, Bayesian methods allow to specify prior information via the selection of a prior distribution $\pi(\boldsymbol{\theta})$ for the unknown model parameters $\boldsymbol{\theta}$. After data observation, based on the likelihood function $L(\mathbf{Y}|\boldsymbol{\theta})$, the updated prior knowledge results in a posterior distribution $\pi(\boldsymbol{\theta}|\mathbf{Y}) \propto L(\mathbf{Y}|\boldsymbol{\theta})\,\pi(\boldsymbol{\theta})$, on which the Bayesian estimations $\hat{\boldsymbol{\theta}}$ are determined, i.e.

$$\hat{\boldsymbol{\theta}} = \int \boldsymbol{\theta}\,\pi(\boldsymbol{\theta}|\boldsymbol{Y})\,d\boldsymbol{\theta}.$$

Hence, we propose a parametric Bayesian MLM with model parameters $\boldsymbol{\theta} = (\boldsymbol{\beta}, \boldsymbol{u})$ (Goldstein, 2011, chap.4), as a particular case of the more general Bayesian multinomial mixed Logit model proposed in Carota et al. (2017). Therefore, similarly, we assume a normal prior distribution for the fixed ($\boldsymbol{\beta}$) and random ($\boldsymbol{u}$) effect model parameters with mean and (co)variance, respectively, $(\mu_{\boldsymbol{\beta}}, \Sigma^2_{\beta})$ and $(\mu_{\boldsymbol{u}}, \Sigma^2_{\boldsymbol{u}})$. We enrich the hierarchy proposed in Goldstein (2011) by assigning an Inverse-Wishart (IW) prior distribution to $\Sigma^2_{\boldsymbol{u}}$. Even if some other priors less informative than the IW can be considered (see, e.g. Hadfield, 2016; McCulloch and Rossi, 2000), the selection of a IW also satisfactorily deals with separation problems while still preserving invariance principles which reduce estimation complexity. Moreover, such a prior is a multivariate generalization of the scale inverse-χ^2 distribution (Gelman et al., 2014) and allows use to be made of the conjugate prior distribution, i.e. a normal-inverse-Wishart.

We select non-informative priors for all model parameters, with a very large variance to reflect the relative lack of confidence about the mean assumed for the fixed and random effect priors (Finch et al., 2014, chap.9).

Therefore, the posterior for $\boldsymbol{\beta}$, $\boldsymbol{u}$ and $\Sigma^2_{\boldsymbol{u}}$ is

$$\pi\left(\boldsymbol{\beta}, \boldsymbol{u}, \Sigma^2_{\boldsymbol{u}}|\boldsymbol{Y}\right) \propto \prod_{k=1}^{K}\prod_{r=1}^{R_k} L(Y_{kr}|\boldsymbol{\beta}, u_k)\pi(\boldsymbol{\beta})\pi(u_k|\mu_{\boldsymbol{u}}, \Sigma^2_{\boldsymbol{u}})\pi(\Sigma^2_{\boldsymbol{u}}). \tag{2}$$

However, sampling from (2) and obtaining marginal posterior distributions need further techniques. Our estimation is based on the MCMC method with a block Gibbs sampler algorithm (Casella and George, 1992) widely used in Bayesian statistics to update model parameters given a level of efficiency and computation tractability higher than the general Metropolis-Hastings algorithm (Hadfield, 2010). The block Gibbs sampler can easily approximate the properties of the marginal posterior distributions, as desired, by sampling from the conditional posterior distribution of each model parameter (see Appendix A).

Finally, model comparison is done, in the classical framework, via the Akaike information criterion (AIC) while, in the Bayesian one, using the deviance information criterion (DIC).

5 Results

The estimated models are conceived so as to include demographic, social, attitudinal and geographical factors assumed to impact on switching behavior. In addition, estimates take into account individual and household heterogeneity. Switching probability is first estimated under a simple logistic regression model with household variables (Table 4).

The model adds several explanatory elements to the variables that are traditionally used to explain switching behavior (see Table 2). At the individual level, in addition to age, and education (degree and diploma), we include gender. In order to capture the effect of horizontal integration we account for the importance of joint (electricity and gas) switching. Finally, we also test for the importance of the market concentration rate at the regional level (W_CR3). Concentration is considered as a possible constraint on the set of choices available to consumers. At the family level, we consider numerosity as a proxy for the relevance of the electricity bill, the size of the municipality of residence as a proxy for the dimension of social interaction, and a self-declared satisfaction with economic resources as a proxy for income. Due to the uneven geographical distribution of the variables, we also include a geographical classification to capture localisation effects.

The results confirm that switching is strongly driven by the structure of the market. The electricity switching rate is strongly related with gas churning. This coefficient captures two different phenomena. First, on the supply side, it shows that horizontally integrated firms experience an advantage in that they can propose joint switching and exploit the spillovers of joint marketing campaigns. Secondly, on the demand side, it shows that if sequential switching is taken into account, once the consumer has learnt how to switch retailers in one market, s/he may apply the same decision process to other services.

As expected, the age of the contact person - the head of the family as resulting from the registry office - negatively affects the switch: elderly people are less prone to face changes that involve contractual conundrum, or they may have developed loyalty to a retailer through longer-term relationships. In policy, the lack of information is considered one of the main barriers to active and efficient behavior (European Commission, 2015). However, in the estimation, satisfaction with the electricity information provided has a negative impact on switching. This evidences consumers' awareness of the problems related with the supply side of the markets as described in Section 3.2: switching to the free market is not as beneficial as expected. The increase in the number of household members, as a proxy for the amount of energy consumption and bills, increments the switching. The coefficient can be interpreted as an attempt to save on electricity bills. We accounted for regional differences by including geographical indicators (NUTS1) that denote wide areas characterised by cultural and institutional features. The introduction of local variables, such as municipality size and regional retail market concentration (W_CR3 calculated at the NUTS2 level) is intended to preserve institutional heterogeneity within the same geographical area. Municipality size does not affect household switching, differently from location. With respect to the North-West, location in southern Italy has a negative effect on switching probability, whereas location in the Islands has positive effects mainly driven by Sardinia. The concentration metric (CR3) has no effect on the switching probability. The same holds for household economic resources.

We preserved the highest possible level of information by conducting a second analysis which fitted individual information. Table 5 shows that, among the newly added information, only the use of the Internet is significant and displays a positive sign. The use of the Internet reflects access to a general source of information (i.e. not limited to contract and service) and the attitude – i.e. frequency – to (general) information seeking. The idea behind the use of this variable is that accessing the Internet provides more detailed information on the service but also gives more distant related information (forthcoming reforms in the sector, political or environmental issues) that enriches consumer awareness. It has been shown that fear arousal concerning climate change issues has a positive effect on the intention to switch to green energy (Hartmann et al., 2016), and that environmentally aware individuals are more willing to switch to dynamic tariffs when environmental benefits are disclosed (Buryk et al., 2015). At the same time, accessing the Internet increases the exposure to advertisements that often show up in seemingly unrelated contexts. In addition, we identify some location effects. Living in a small municipality (< 10000 inhabitants) induces an increment in switching with respect to living in a metropolitan area. The effect suggests that in small communities peer pressure and imitation have a stronger conditioning effect. Finally, economic resources, a qualitative proxy for income, signal that higher incomes are associated with lower switching probabilities, which suggest that incentives to save are less stringent for wealthier individuals.

A simple logistic regression does not account for household heterogeneity. However, the introduction of a random effect to cope with heterogeneity results in a quasi complete separation problem which precludes a Newton-Raphson convergence. Hence, we applied the Bayesian method illustrated in Section 4 based on 115000 iterations with a burn-in equal to 20000 and a thinning interval equal to 10. Table 6 confirms the main results of the previous analyses. We also observe the negative effect of market concentration. This

Table 3: Variables description

	Dependent variable
Electricity_retailer_switch	Dummy variable: 1 for families that switched electricity retailer between July 2007 - end of Jan 2014
	Explanatory variables
Female	Dummy variable: 1 for female
Over65	Dummy variable: 1 for individuals with age > 65
Over65_CP	Dummy variable: 1 for contact person with age > 65
Degree	Dummy variable: 1 for individuals with a university degree as highest educational level
Diploma	Dummy variable: 1 for individuals with a diploma as highest educational level
Nb_members	Number of family members
Inhab	Categorical variable: municipality size, with levels Metropolitan Area, < 10000 inhabitants, > 10000 inhabitants
Geo	Categorical variable: geographical distribution (NUTS1), with levels North-West, North-East, Centre, South, Islands
Econ_resources	Dummy variable: 1 for satisfactory level of economic resources
Frequent_Internet_user	Dummy variable: 1 for individuals that navigate the Internet more than once a week
Gas_retailer_switch	Dummy variable: 1 for families that switched gas retailer between July 2007 - end of Jan 2014
Sat_info_level	Dummy variable: 1 for contact person that reports having satisfactory information on electricity service and provision
W_CR3	Dummy variable: 1 for regional market concentration (CR3) > national weighted average (weights = regional populations)

result encourages the inclusion of market variables (other than prices) in estimations of switching rates.

On the methodological side, the Bayesian approach can produce more accurate estimates than the classical approach (see Carota et al., 2017). However, due to the quasi complete separation problem and to the introduction of the extra variability associated with household heterogeneity, we are not able to compare confidence and credibility intervals[16] of the point estimates reported in Table 5 and 6. We therefore indirectly compare them via forest plots (see Figure 5). It can be seen that the Bayesian estimates are consistent with the classic ones and that, for the individual variable estimates with random effects, the Bayesian method results in tighter credibility intervals.

Table 4: Logistic regression at household level

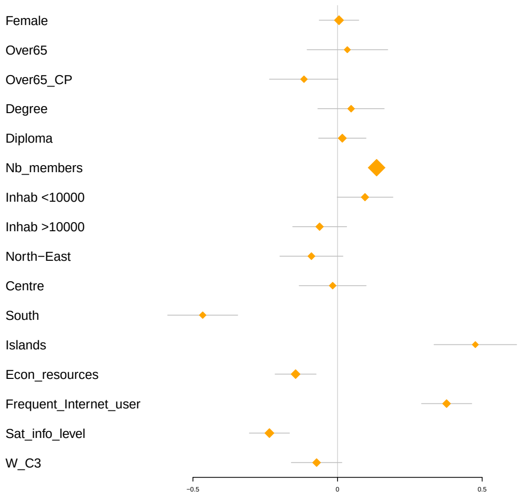
	Dependent variable:			
	Electricity_retailer_user			
	(1)	(2)	(3)	(4)
Over65_CP	-0.256^{***}	-0.252^{***}	-0.258^{***}	-0.254^{***}
	(0.057)	(0.058)	(0.058)	(0.058)
Nb_members	0.181^{***}	0.183^{***}	0.181^{***}	0.183^{***}
	(0.021)	(0.021)	(0.021)	(0.021)
Inhab <10000	0.077	0.085	0.083	0.092
	(0.071)	(0.071)	(0.071)	(0.071)
Inhab >10000	−0.072	−0.069	−0.075	−0.073
	(0.069)	(0.069)	(0.069)	(0.069)
North-East	−0.115	−0.107	−0.094	−0.084
	(0.077)	(0.077)	(0.080)	(0.080)
Centre	0.021	−0.003	0.049	0.028
	(0.079)	(0.079)	(0.084)	(0.085)
South	-0.561^{***}	-0.571^{***}	-0.519^{***}	-0.523^{***}
	(0.078)	(0.078)	(0.090)	(0.091)
Islands	0.424^{***}	0.398^{***}	0.479^{***}	0.460^{***}
	(0.087)	(0.087)	(0.105)	(0.106)
Econ_resources	−0.065	−0.050	−0.063	−0.048
	(0.051)	(0.052)	(0.051)	(0.052)
Gas_retailer_switch	3.680^{***}	3.667^{***}	3.676^{***}	3.663^{***}
	(0.066)	(0.066)	(0.066)	(0.066)
Sat_info_level		-0.175^{***}		-0.175^{***}
		(0.052)		(0.052)
W_CR3			−0.060	−0.067
			(0.065)	(0.065)
Constant	-2.615^{***}	-2.520^{***}	-2.608^{***}	-2.513^{***}
	(0.095)	(0.100)	(0.095)	(0.100)
Observations	18,448	18,244	18,448	18,244
Log Likelihood	−5,616.710	−5,553.786	−5,616.277	−5,553.256
Akaike Inf. Crit.	11,255.420	11,131.570	11,256.560	11,132.510
McFadden	0.2818	0.2818	0.2809	0.2809
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 5: Logistic regression at individual level

	Dependent variable:			
	Electricity_retailer_user			
	(1)	(2)	(3)	(4)
Female	0.004	0.005	0.005	0.005
	(0.035)	(0.035)	(0.035)	(0.035)
Over65	0.032	0.033	0.033	0.034
	(0.071)	(0.071)	(0.071)	(0.071)
Over65_CP	-0.112^{*}	-0.114^{*}	-0.114^{*}	-0.116^{*}
	(0.060)	(0.060)	(0.060)	(0.060)
Degree	0.048	0.043	0.052	0.047
	(0.058)	(0.058)	(0.058)	(0.059)
Diploma	0.014	0.013	0.017	0.016
	(0.042)	(0.042)	(0.042)	(0.042)
Nb_members	0.134^{***}	0.136^{***}	0.134^{***}	0.135^{***}
	(0.015)	(0.015)	(0.015)	(0.015)
Inhab <10000	0.080^{*}	0.088^{*}	0.088^{*}	0.095^{*}
	(0.049)	(0.049)	(0.049)	(0.049)
Inhab >10000	−0.062	−0.058	−0.066	−0.062
	(0.047)	(0.048)	(0.047)	(0.048)
North-East	-0.119^{**}	-0.115^{**}	-0.095^{*}	−0.090
	(0.053)	(0.054)	(0.055)	(0.056)
Centre	−0.021	−0.051	0.013	−0.017
	(0.055)	(0.055)	(0.059)	(0.059)
South	-0.503^{***}	-0.518^{***}	-0.452^{***}	-0.466^{***}
	(0.053)	(0.053)	(0.061)	(0.062)
Islands	0.442^{***}	0.409^{***}	0.509^{***}	0.476^{***}
	(0.059)	(0.060)	(0.072)	(0.073)
Econ_resources	-0.171^{***}	-0.146^{***}	-0.169^{***}	-0.145^{***}
	(0.036)	(0.036)	(0.036)	(0.036)
Frequent_Internet_user	0.385^{***}	0.377^{***}	0.385^{***}	0.377^{***}
	(0.044)	(0.044)	(0.044)	(0.044)
Gas_retailer_switch	3.652^{***}	3.634^{***}	3.648^{***}	3.629^{***}
	(0.045)	(0.045)	(0.045)	(0.045)
Sat_info_level		-0.236^{***}		-0.236^{***}
		(0.035)		(0.035)
W_CR3			−0.072	−0.072
			(0.044)	(0.045)
Constant	-2.701^{***}	-2.561^{***}	-2.696^{***}	-2.557^{***}
	(0.080)	(0.083)	(0.080)	(0.083)
Observations	37,217	36,814	37,217	36,814
Log Likelihood	−11,942.520	−11,823.410	−11,941.190	−11,822.090
Akaike Inf. Crit.	23,917.030	23,680.810	23,916.380	23,680.170
McFadden	0.2847	0.2848	0.2833	0.2834
Note:				*p<0.1; **p<0.05; ***p<0.01

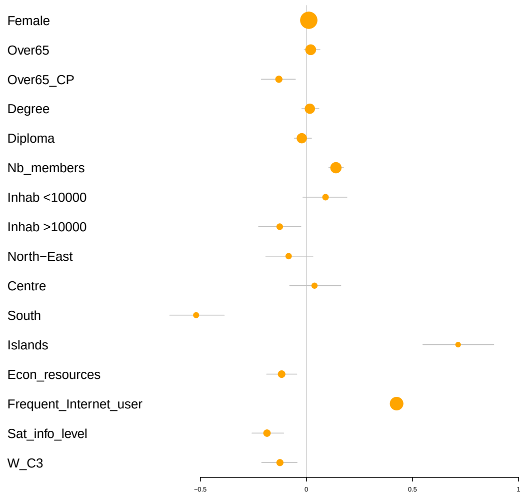
Table 6: Bayesian mixed Logit model

	Dependent variable:			
	Electricity_retailer_switch			
	(1)	(2)	(3)	(4)
Female	0.041	-0.030^{*}	0.029	0.011
Over65	0.064^{***}	0.072	0.078	0.020
Over65_CP	-0.224^{***}	-0.093	-0.308^{***}	-0.130^{***}
Degree	-0.048	0.087	0.102^{*}	0.016
Diploma	-0.018	0.102^{**}	0.051	-0.022
Nb_members	0.183^{***}	0.195^{***}	0.238^{***}	0.139^{***}
Inhab <10000	0.107^{**}	0.109^{*}	0.196^{**}	0.090
Inhab >10000	-0.090^{*}	-0.017	-0.050	-0.126^{**}
North-East	-0.123^{**}	-0.233^{***}	-0.112	-0.084
Centre	0.099	-0.062	0.100	0.038
South	-0.569^{***}	-0.755^{***}	-0.613^{***}	-0.520^{***}
Islands	0.609^{***}	0.354^{***}	0.826^{***}	0.715^{***}
Econ_resources	-0.011	-0.177^{***}	-0.228^{***}	-0.117^{***}
Frequent_Internet_user	0.250^{***}	0.317^{***}	0.332^{***}	0.425^{***}
Gas_retailer_switch	5.573^{***}	5.772^{***}	7.046^{***}	5.503^{***}
Sat_info_level		-0.187^{***}		-0.186^{***}
W_CR3			-0.159^{**}	-0.125^{***}
Constant	-3.999^{***}	-3.946^{***}	-4.949^{***}	-3.715^{***}
Observations	37,217	36,814	37,217	36,814
Deviance Inf. Crit.	11,708.950	11,590.080	10,576.810	10,565.40
Note:		*p<0.1; **p<0.05; ***p<0.01		



(a) Logistic regression

(Table 5)



(b) Bayesian GLMM

(Table 6)

Figure 5: Forest plots report, respectively, confidence intervals and credibility intervals for each variable. Box size is based on precision.

6 Concluding remarks

The paper contributes to the assessment of the functioning of liberalized markets by providing the first detailed analysis of switching in the Italian retail electricity market. The aim of the Three Energy Packages promulgated by the EU was to expand the benefits deriving from the removal of non-tariff barriers. In particular, a free market should have guaranteed a higher consumer surplus, systemic efficiency, and a sustained rate of innovation. The evidence from mid-term evaluations is mixed: it ranges from more optimistic views that observe prices competition (Fehr and Hansen, 2010) to more concerned assessments stressing that price reductions have benefited mostly large customers and left small firms and domestic customers unaffected (Concettini and Créti, 2013). There are several indicators that measure the effects of competition on efficiency and innovation, but in the absence of a criterion to establish their relative weight (IPA, 2015, p. 46), precise global evaluations and comparisons are indeed difficult. Among the many indicators, this paper has focused on switching rates as an index of consumer participation. Switching behavior is currently under the spotlight of the European institutions. The completion of liberalization has given consumers the chance to "shop around" and, indirectly, it has invested them with responsibility for feeding competitive pressure. Indeed, active consumers can switch to better contractual conditions, thereby forcing retailers to provide better services at cheaper fares.

Estimates of the switching probability account for different aspects of the decision-making process. Individual and household variables describe demographic, social, economic and geographical factors. The regional market variable (W_CR3) captures different levels of competitiveness. The analysis is conceived so as to preserve data heterogeneity while highlighting common patterns. The dual role for information, specific vs. general, points to the extension of the notion of relevant information beyond that strictly related to the provision of electricity (alternative offers, terms of contract, smart devices). Access to the Internet is confirmed as a strategic factor that improves consumer engagement. The importance of joint switching together with the negative impact of market concentration testify to the importance of market structure.

The overall assessment of the Italian market casts doubt on the effective benefits deriving from liberalization. Free market prices are on average higher than those proposed on the regulated market in spite of a sustained rate of entry in the sector. Moreover, households that have switched are less satisfied than the ones that have stayed with the previous provider. In Southern Italy, households are less satisfied with services provided than households located in the North, but switching rates remain lower than in the rest of the peninsula. The uneven geographical distribution of the variables suggest that liberalization should encompass wider institutional and social scenarios.

Notes

[1]In the Italian electricity market, the maximum saving associated with fixed-price offers, calculated on spring data, was about €130 before tax per year in 2013. For gas provision, the maximum saving, under the same conditions, was about €260. Source: TrovaOfferte. AEEGSI, 2015, pp. 47-92. Maximum yearly expenditure is €593.3 and €1581.4 for electricity and gas respectively.

[2]First Package, 1996: Directive 96/92/EC; Second Package, 2003: Directive 2003/54/EC; Third Package, 2009: Directive 2009/72/EC.

[3]Currently under discussion by the Italian Parliament.

[4] In the same year, in the Danish market consumers awareness was around 50% (Yang, 2014).

[5]In 2013, Great Britain, Ireland, Norway and the Netherlands exhibited switching rates in their electricity markets higher ($> 10\%$) than in the majority of the other European countries.

[6]Respondents were asked if they had switched at least once in the previous seven years.

[7]The number of active groups rose from 219 for 2012 to 260 for 2013. As regards the number of retailers, 136 subjects operate on the regulated market, 3 in the safeguarded categories market, and 336 in the free market. With respect to 2012 the total number of operators has grown by 50 units. All the new entrants operate on the free market (AEEGSI, 2014).

[8]The Herfindahl index is 2810 (AEEGSI, 2014).

[9]Hilke (2008) analysis of the U.S. electricity market describes similar patterns.

[10]See footnote 7.

[11]Note that Train (2003) and references therein inspire the methodological section. For

ease of exposition, we do not report this reference in the rest of the discussion. Therefore, see chap. 6 and 12 Train (2003) respectively for an illustration of the mixed Logit model and of its Bayesian version. Regarding the latter, Carota et al. (2017) show a more general case.

[12]The mixed Logit model allows for random taste variation, unrestricted substitution patterns, and correlation in unobserved factors.

[13]Note that in any logistic regression model the log-likelihood function is globally concave, therefore the function can have at most one global maximum.

[14]To the best of our knowledge, for a first application and comparison see Carota et al. (2017). Alternatively, random coefficients can be simply considered as part of the utility error component, inducing correlations among alternative utilities.

[15]Therefore each fixed or random effect is treated as a random variable.

[16]The classic approach assumes that there are fixed and unique model parameter values and, to make inferences on them, experiments are conducted so that a confidence interval will be constructed to express knowledge uncertainty after the experiment. The Bayesian approach assumes fixed parameter values endowed with a suitable prior. It follows that credibility intervals have fixed bounds and random estimated parameters. Confidence intervals treat the estimated value as fixed and the bounds as random variables, without incorporating prior knowledge. Forest plots (or Blobbograms), which are frequently used in meta-analysis, are used here to compare method and model accuracy (see Carota et al., 2017).

A Posterior for the block Gibbs sampling

The conditional posteriors for the block Gibbs sampling of the proposed Bayesian mixed Logit model, following Train (2003) and Carota et al. (2017):

$$
\begin{aligned}
&\pi(\boldsymbol{u}|\boldsymbol{\beta}, \mu_{\boldsymbol{u}}, \Sigma^2_{\boldsymbol{u}}) \propto \prod_{k=1}^{K}\prod_{r=1}^{R_k} L(Y_{kr}|\boldsymbol{\beta}, u_k, \Sigma^2_{\boldsymbol{u}}) N(u_k|\mu_{\boldsymbol{u}}, \Sigma^2_{\boldsymbol{u}}) \\
&\pi(\Sigma^2_{\boldsymbol{u}}|\boldsymbol{u}) \sim \mathsf{IW}(\mathsf{M}+N, (\mathsf{MI}+NS)/(\mathsf{M}+N)) \\
&\pi(\boldsymbol{\beta}|\boldsymbol{u}) \propto \prod_{k=1}^{K}\prod_{r=1}^{R_k} L(Y_{kr}|\boldsymbol{\beta}, u_k)\pi(\boldsymbol{\beta}).
\end{aligned} \tag{3}
$$

Where M and I are the IW parameters and $S = (\boldsymbol{u} - \mu_{\boldsymbol{u}})(\boldsymbol{u} - \mu_{\boldsymbol{u}})^T/N$.

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