A regression model to assess the social acceptance of demand response programs

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Abstract. Residential demand response has been playing an important role in the low carbon energy system transition. Although this is not a new concept, the popularity of Demand Response (DR) programs is growing, driven by the increasing opportunities that emerged with smart grid appliances as well as by their potential to support the integration of variable renewables generation. The end-user plays a key role in the successful deployment and dissemination of these DR programs. This study aims to assess social awareness and acceptance of DR programs, based on a survey for data collection and complemented with the regression models. The results suggest that the economic determinants, contribution to environmental protection as well as the extent of urbanization are important motivating drivers, to be explored in the future to encourage the residential consumers' participation in DR programs.

Keywords: Demand Response; Social Acceptance; Heterogeneous Choice Model (oglm); Ordered Logit Regression (ologit); Residential consumers

1 Introduction

Residential demand response has been playing an important role in the low carbon energy system transition [1]. Demand Response (DR), involves achieving changes in energy usage by end-users' customers', for instance, shifting demand from peak to off-peak demand periods. This change can be achieved through price signal, providing financial incentives for shifting the electricity usage for the demand periods when the electricity price is lower, based on the higher share of RES for electricity generation; direct control [2]; and automation of appliances [3]. DR is also referred to as a potential driver for mitigating the challenges of reducing the intermittency of renewable sources by reducing demand at times of low renewable supply and increasing the demand at times a surplus of renewable energy is available.

DR is not a new concept. However, it still has a limited role and electricity supply and demand are mainly balanced by ensuring that generation, reserves, and network capacity are sufficient to meet demand [4]. The expected large-scale electrification of the transportation and heating sectors should have a significant impact on the energy consumption and has been creating a growing interest on demand flexibility for market

players and energy policies. In this context, the residential consumers' participation in DR programs could play an important role in the electricity system management.
Several publications have explored household responsiveness to demand-side management. For, instance, [5] used ordered logistic regression to estimate the tiered electricity pricing system (TEP) effectiveness and the results suggest this system helps to reduce the electricity expenditures in China; another relevant aspect noted was a significant and negative association between the TEP effectiveness and income as this effectiveness tends to be reduced for high income groups. The regression results revealed that sociodemographic characteristics play an important role in improving the tiered electricity pricing effectiveness. Also for China [6], a binary logistic regression was used to demonstrate if the survey respondents were willing to accept the peak and off-peak time pricing. The socioeconomic characteristics and the level of knowledge on the topic were found to be significant for the acceptance of tiered pricing with females and elderly consumers showing higher acceptance. Another study, applied to the United Kingdom (UK), [7] using ordered logit regression, examined the willingness of the respondents to switch from flat-rate electricity tariff to ToUs tariff. The authors concluded that this willingness was driven by differences in loss-aversion characteristics and ownership of demand flexible appliances rather than by socioeconomic and sociodemographic characteristics.
In this paper, we propose a methodology to assess the social awareness and acceptance of DR programs, based on a survey for data collection in Portugal. From the collected data, the proposed regression model was derived, aimed at determining the most critical drivers to encourage domestic consumers' participation in DR programs and their level of acceptance using an ordered scale "totally disagree" "tend to disagree" "tend to agree" and "totally agree".
This paper is set out as follows: Section 2 is dedicated to describing both the data and methodology used. Section 3 presents the results of the various determinants for electricity usage delaying. Finally, in section 4, the conclusions and future remarks are presented.

2 Data sources and methodology

2.1 Sample Data sources

This study uses an empirical research method in order to assess the social awareness and acceptance of DR programs. We attempt in particular to address (i) the motivational factors to delay the electricity use (ii) the perceived flexibility of the residential electricity users through the quantification of the acceptance of delay on the use of appliances and (iii) willingness to accept the automatic control of the heating and cooling system. The data for this study was obtained from a survey conducted by phone during May and June of 2018, in Portugal. The survey was administered to residents randomly selected from 278 total number of Portuguese municipalities, covering both rural and urban areas. The analysis only considers Continental Portugal (i.e., excluding Azores and Madeira Islands). In total, 385 valid responses were obtained, which ensured a 95%

confidence degree with a 5% margin of error. Table 1 presents a description of the variables used in the study.

Table 1. Description of variables encoded into the Stata software

	Variables	***Variables assignment***
Sociodemographic characteristic	Gender	Female =1, Male =2
	Age	[18-24] = 1, [25-44] = 2, [45-64] =3, above 65 years old = 4
	Education	Low =1; Medium=2; High=3
	Professional activity	Unemployed=1, Student=2, Posted worker=3, Self-employed worker=4, Retired= 5, Domestic worker=6
	Household size	Numeric
	Urban/ Rural	Rural =1, Urban=2
Knowledge and dynamism on electricity consumption	ToUs tariffs	No familiar with ToUs tariff= 0, Familiar with ToUs tariff =1
	Reading meter	No regular meter reading= 0, Meter reading =1
	Switch electricity supplier	No switch of electricity supplier = 0, Switch electricity supplier=1
	Smart meter	No ownership of a smart meter= 0, Ownership of smart meter=1
Motivational factors for energy management	Environmental factors	"Doesn´t know/ doesn´t answer" =0, " Totally disagree"=1, "Tend to disagree"= 2, "Tend to agree"=3 "Totally agree"=4
	Reduce energy imports	"Doesn´t know/ doesn´t answer" =0, " Totally disagree"=1, "Tend to disagree"= 2, "Tend to agree"=3 "Totally agree"=4
	Reduction of electricity bill	"Doesn´t know/ doesn´t answer" =0, " Totally disagree"=1, "Tend to disagree"= 2, "Tend to agree"=3 "Totally agree"=4
	Recommendation	"Doesn´t know/ doesn´t answer" =0, " Totally disagree"=1, "Tend to disagree"= 2, "Tend to agree"=3 "Totally agree"=4

2.2 Methodology

Figure 1 presents the modelling structure used in the study following five different stages:

Stage 1:

Bearing in mind the purpose of this study, a logistic regression was applied. According to the classification of dependent variables, ordinal response with a meaningful sequential order, Ordered Logit regression (ologit), or Ordered Probit regression (oprobit), which are based on the cumulative probabilities of the response variable are the most suitable regressions to be applied. According to Ref. [8], logit regression has two main advantages: (i) simplicity – the equation of logistic distribution function is simple, while on the other and, the equation of probit distribution function contains unquantified integral and (ii) – the interpretation of the coefficients is directly presented as logarithms of chances (probability), while in the probit regression the interpretation of the coefficients is not direct. The logit and probit models are very similar in terms of predictive accuracy. Logit regression was then decided to be employed (highlighted in orange in 1st stage of Figure 1).

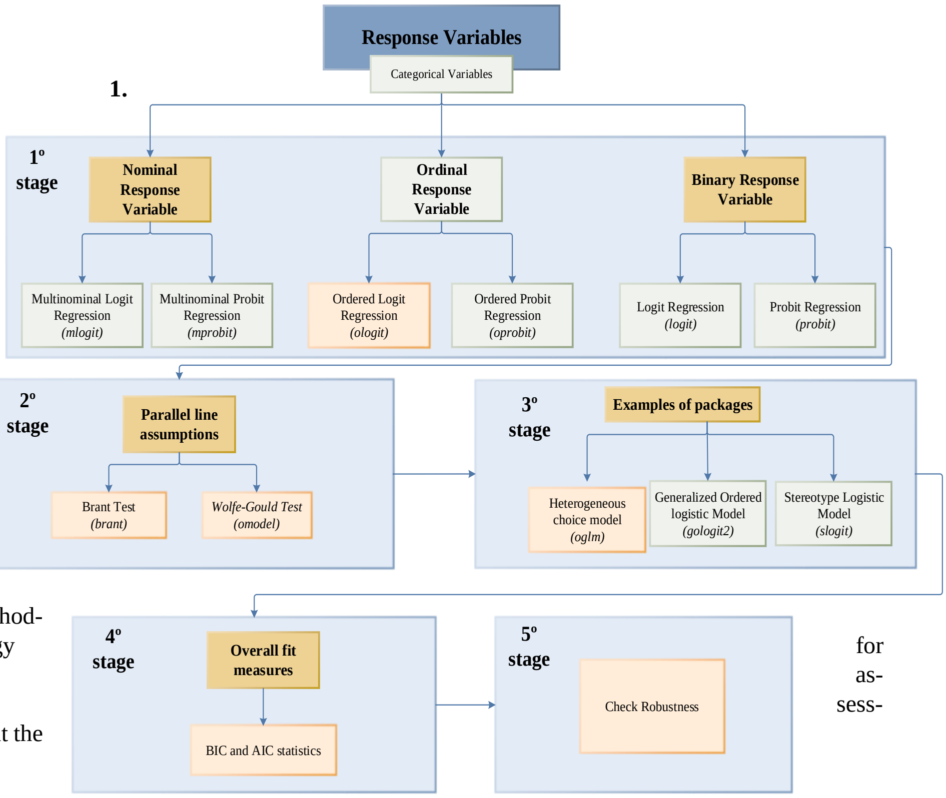

Fig. 1. Methodology for assessment the acceptance of DR programs

Stage 2:

After introducing the traditional ordered logit model, the assumption of the Ordered Logit regression was discussed in this second stage. According to the [9] this assumption is recurrently violated. The violation of the proportional odds/parallel lines assumption could lead to the formulation of an incorrect or mis-specified model. To validate the use of the Ordered Logit regression, we need to ensure the proportional odds/parallel lines assumption. For this purpose, the Brant and Wolfe-Gould tests were performed [10]. A Brant test provides both a global test to check whether any variables violates the proportional odd/parallel-lines assumption, as well as a test of the assumption for each variable considered [11]. Brant test suggested that the proportional odd/ parallel lines assumptions of the different dependent variables considered in the study was significantly violated (p-value) <.0.05). The only exception was for the dependent variable recommendation (p-value= 0.227), as p-value is higher than 0.05 the proportional odd/ parallel lines assumptions were not violated. The Wolf e-Gould test was used to confirm the results obtained by Brant test and led to similar conclusions.

Stage 3:

Given the violation of the assumptions for the traditional ordered logit model, the possibility of using generalized ordered logit regression with a logistic cumulative distribution function was considered. However, according to Ref. [12] it is recommended to compute the predicted probabilities under gologit2 command in order to verify whether this statistical technique is appropriate. This ends up highlighting the problem of negative probabilities, as a result of the model application to our data. Other studies such as [13] also reached negative probability values and [14] offer some explanation for this somehow puzzling outcome, which may be related to a high standard error on the responses.

Given these limitations, a heterogeneous choice model is an interesting model to be applied as it explicitly specifies the determinants of heteroskedasticity in an attempt to correct it. Besides this, these models also are useful when the variability of underlying attitudes itself has importance [15] as the case of this study. The heterogeneous choice model has been proposed as an extension of the logit and probit models. This model discloses how the choice and variance equations are combined to come up with the probability of any response.

Stage 4:

The results of the 2^{nd} stage indicate that the assumption of the ordered logit model is indeed violated for this analysis, as Brant and Wolf-Gould tests indicate that the variables do not meet the proportional odds/parallel lines assumption requirement. However, this does not necessarily mean that data are suitable for the heterogeneous choice model. Therefore, oglm's stepwise selection was applied in order to identify the variables that cause the assumption of heteroskedastic errors to be violated. In particular, the inclusion of heteroskedasticity parameters improves the overall model fit substantially. This improvement is evidenced by the Bayesian Information Criterion (BIC) and Akaike's Information Criterion (AIC) statistics. The aim of using fit measures is to compare the relative plausibility between two different models: the heterogeneous choice model and stereotype logistic regression (slogit) in order to find the best model (4^{th} stage of Figure 1). BIC measure evaluates the overall fit of the models. AIC measure is used to compare the models across the different samples [16]. These measures are defined as:

$$BIC = -2 * ln(LL) + 2 * k \tag{1}$$

$$AIC = -2 * l(LL) + ln(N) * k \tag{2}$$

Where LL is the log-likelihood, k is the number of parameters estimated and N is the number of observations

The results pointed to the heterogeneous choice model as the most suitable one as highlighted in orange in 3rd stage of Figure 1.

Stage 5:

The results of the 5th stage use a common practice to the estimated model robustness by analysing if coefficients change the effect (positive or negative) when the regression model is modified. The comparison derived from the empirical analysis of the estimation of the three models: heterogeneous choice model (ogml) stereotype logistic regression (slogit) e generalized ordered logit regression (gologit2). As no significant difference was found on the estimated coefficients, the chosen model (heterogeneous choice model) could be considered robust and the results can be interpreted as a true casual effect between explained variable and explanatory variables.

3 Results

In this section, we present the models obtained from empirical analysis, which allow obtaining the response (dependent variable) predicted by the respondent's answers (independents variables). Based on the above mentioned, we conducted a heterogeneous choice model and ordered logit regression (which are both applied for ordinal dependent variables) using the commands oglm and ologit in the statistical software Stata 15. Accordingly, Table II shows the results of the estimated coefficients. The significance of the coefficients of variance equations may be relevant enabling to measure the variability attitudes towards end-user's participation in DR programs.

Table II discloses the results for the motivational factors for participating in energy management programs.

Regarding the environmental determinants, a positive coefficient in the variance equation suggests that respondents living in large households tend to present less disperse or variable attitudes towards participating in DR programs. On the other hand, in regarding the reduction of electricity bill determinant, a negative coefficient in the variance equation reveals that older people tend to present less disperse or variable responses when compared to young people. Moreover, the variability in attitude towards environmental benefit declined across the value of electricity bill meaning that respondents paying larger bills will tend to present less variable responses. Additionally, respondents who own a smart meter tend to present higher variability on the value assigned to environmental benefit; this could be explained by the fact that respondents who own a smart meter are more focused on financial incentives than to benefit the environment. The results presented by the equation of choice are interpreted the same way as a traditional logistic regression. Therefore, the results suggest that a large household and the knowledge of the possibility to shift from flat tariff to ToUs tariff influence positively the respondents do defer their electricity consumption motivated by environmental determinants.

The women and people who live in rural areas are more likely to accept to shift their electricity consumption encouraged by the potential financial gains. The negative coefficients in the variance equation reveal that the variability of the responses for older people and large household is lower than for younger respondents living in small households. A positive coefficient in variance equation suggests that the group of people who have knowledge on ToUs tariff and who regularly communicate with the electricity supplier tend to present more disperse responses in what concerns their attitudes towards deferring the electricity usage motivated by the financial issues. A large household could have a positive effect do defer the electricity consumption motivated by the contribution to reducing dependence on imported energy or by following acquaintance recommendation. The female gender and again the familiarity on ToUs are significant factors for the choice equation showing that these groups tend to be more sensitive to the energy dependence argument to participate in DR programs.

Table 2. Aggregation analysis for motivational factors for energy management

Regression models		**Heterogeneous choice model (oglm)**			**Ordered logit regression (ologit)**
Motivational factors for energy management		**Environmental factors**	**Reduction of electricity bill**	**Reduce energy imports**	**Recommendation**
			Equation CHOICE		
Sociodemographic determinants	Male	-0.273	-0.297*	-0.537*	-0.041
	Age	0.056	0.034	0.257	0.050
	Professional activity	0.072	0.072	0.083	0.093
	Education level	0.046	0.020	0.287	0.059
	Household size	0.360***	0.022	0.416***	0.145*
	Rural area	0.200	0.275*	0.296	0.138
	ToUs	0.483*	0.261	0.627**	0.434
Knowledge and dynamism of the respondents	Reading meter	-0.149	-0.048	0.357	-0.020
	Switch electricity supplier	0.033	0.072	-0.011	0.045
	Smart meter	0.740	0.346	0.886	0.331
Electricity bill value	Electricity bill value	-0.135	0.054	0.218	-0.011

Equation VARIANCE					
Sociodemo-graphic determi-nants	Male	-	-	0.331***	-
	Age		-0.330***		-
	Profes-sional activity	-	-		-
	Education level	-	-		-
	House-hold size	0.114*	-0.162**		-
	Rural area	-	-	0.411***	-
	ToUs	-	0.594***		-
Knowledge and dynamism of the respondents	Reading meter	-	0.348*		-
	Switch electricity supplier	-	-		-
	Smart me-ter	0.626**	-	0.506**	-
Electricity bill value	Electricity bill value	-.184**	-		-
Cut- points	/cut1	-0.597	-0.135		-1.085
	/cut2	-0.108	-0.086		0.110
	/cut3	0.599	0.208		1.132
	/cut4	1.817***	0.688		2.541
	N	385	385		385
	Pseud R2	0.0327	0.0658		0.0082
	LR test (Chi2)	35.01***	60.48***		9.58
	Log-like-lihood	-518.28626	-429.49223		-580.53897
	AIC		896.9845		1191.078
	BIC		972.0961		1250.377

Note: AIC – Akaike Information Criterion. BIC – Bayesian Information Criterion. The LR test tests the null hypothesis, which states that there was no difference between the model without independent variables and the model with dependent variables. ***, **, and * denote statistical significance level at 1%, 5% and 10%, respectively.

4 Discussion

The active role of women in electricity usage has been an object of analysis in other studies. However, this study found that women tend to be more active than men in the participation of DR programs, as shown in Table 2. The pertinence of these findings is particularly relevant in the Portuguese context, given that activities such as cooking and laundry represent a large share of energy consumption at the household level. These tasks are mainly performed by women, which should be taken into consideration in energy planning. Additionally, such results could also be used to foster shared responsibility at the household level, possibly contributing to balance the energy-related household chores and decision making.

Our results suggest that the household size could be a crucial driver to foster the DR programs, with larger households showing higher interest in participating in these programs as shown in Table 2. An additional member also could encourage positively to reduce electricity consumption. Namely, young children as a result of school education on energy and environmental protection principles could encourage parents and relatives towards a lower carbon lifestyle and more sustainable household patterns. This finding was also suggested by [17].

Another relevant outcome of this paper is the relevance of the monetary and environmental determinants to increase demand flexibility. Rather consensual responses were obtained, when questioned about the possibility to reduce the electricity bill, suggesting that the financial incentives are a crucial determinant for increasing the end-user flexibility demand motivated. This finding is also suggested by the statistical results that state that a large share of the respondent's answer is "totally agree" to defer the electricity usage motivated by the possibility to reduce the electricity bill.

5 Conclusions and policy implications

This current study is focused on the analysis of the social awareness and acceptance of DR programs, based on a survey for data collection complemented with statistical models into the residential sector. In this regard, two different regression models were estimated, the ordered logit regression and heterogeneous choice model, separately. The heterogeneous choice model was performed when the assumption of parallel lines was violated. This can help to avoid errors concerning the statistical significance of the explanatory variables.

From the resulting models, the role of women on electricity demand flexibility could be inferred. This finding is lengthily discussed to promote the participation of women in the decision making of the energy sector. Women are strongly associated with household chores, such as laundry, and the use of domestic appliances such as washing machines and dryers, which have a high potential to increase demand flexibility. The analysis also found that the level of higher education could increase the success of the DR programs, this group is related to the high use of new technologies, which is the first step towards a broad implementation of smart appliances that may support DR programs. Also, DR program implementation seems to be easily accepted by people living in urban areas which can create interesting synergies with the emergence of smart and sustainable cities. The analysis found that the flexibility is greatly linked to cost determinants. It is particularly important that the potential cost saving can somehow compensate for the inconvenience which may arise from the increase in flexibility with impacts on daily routines as well as in the comfort of the household. It is also noteworthy that environmental concerns play an important role in the willingness to participate in DR programs deployment and dissemination.

This study highlights could provide crucial information for energy policy and energy companies in order to define suitable strategies of development for further improvement on the power grid as well as encouraging the end-users to be more flexible. Moreover, the importance assigned to environmental and cost concerns should not be overlooked in the design of programs to increase the level of awareness on demand flexibility. This study should be seen as a first approach to design models that may explain the acceptance and willingness to participate in DR programs, but the complexity of the topic and related questions call attention to the need to proceed with further research on the topic. In particular, it would be important to extend the number of participants to allow for the use of different statistical techniques such as factorial or cluster analysis that could significantly contribute to the debate.

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References

1. B. Parrish, R. Gross, and P. Heptonstall, "On demand: Can demand response live up to expectations in managing electricity systems?," *Energy Res. Soc. Sci.*, vol. 51, no. January, pp. 107–118, 2019.
2. M. H. J. Weck, J. van Hooff, and W. G. J. H. M. van Sark, "Review of barriers to the introduction of residential demand response: a case study in the Netherlands," *International Journal of Energy Research*, vol. 41, no. 6. pp. 790–816, 2017.
3. M. A. R. Lopes, C. Henggeler Antunes, K. B. Janda, P. Peixoto, and N. Martins, "The potential of energy behaviours in a smart(er) grid: Policy implications from a Portuguese exploratory study," *Energy Policy*, vol. 90, pp. 233–245, Mar. 2016.
4. G. Strbac, "Demand side management: Benefits and challenges," *Energy Policy*, vol. 36, no. 12, pp. 4419–4426, 2008.
5. S. Zhang and B. Lin, "Impact of tiered pricing system on China's urban residential electricity consumption: Survey evidences from 14 cities in Guangxi Province," *J. Clean. Prod.*, vol. 170, pp. 1404–1412, 2018.
6. Y. Yang, M. Wang, Y. Liu, and L. Zhang, "Peak-off-peak load shifting: Are public willing to accept the peak and off-peak time of use electricity price?," *J. Clean. Prod.*, 2018.
7. M. Nicolson, G. Huebner, and D. Shipworth, "Are consumers willing to switch to smart time of use electricity tariffs? The importance of loss-aversion and electric vehicle ownership," *Energy Res. Soc. Sci.*, vol. 23, pp. 82–96, 2017.
8. T. Klieštik, K. Ko, and M. Mišanková, "Logit and Probit Model used For Prediction of Financial Health of Company," vol. 23, no. October 2014, pp. 850–855, 2015.
9. R. Williams, "Understanding and interpreting generalized ordered logit models," *J. Math. Sociol.*, vol. 40, no. 1, pp. 7–20, 2016.
10. J. S. Long and J. Freese, Regression Models for Categorical Dependent Variables Using Stata. 2001.
11. R. Williams, "Gologit2: A program for Generalised Logistic Regression manual," pp. 1–18, 2005.
12. R. Williams and N. Dame, "Gologit2 Documentation," *Stata J.*, vol. 6, no. 1, pp. 58–82, 2007.

13. P. J. Cheek, P. McCullagh, and J. A. Nelder, “Generalized Linear Models, 2nd Edn.,” *Appl. Stat.*, vol. 39, no. 3, p. 385, 1990.
14. L. Keele and D. K. Park, Difficult choices: an evaluation of heterogeneous choice models. 2006.
15. R. Williams, “Fitting heterogeneous choice models with oglm,” *Stata J.*, vol. 10, no. 4, pp. 540–567, 2010.
16. R. Williams and N. Dame, “Scalar Measures of Fit : Pseudo R 2 and Information Measures (AIC & BIC) First we present the results for an OLS regression and a similar logistic regression . Incbinary is a dichotomized version of income where the higher half of the cases are coded 1,” pp. 1–16, 2015.
17. I. Aguirre-Bielschowsky, R. Lawson, J. Stephenson, and S. Todd, “Kids and Kilowatts: Socialisation, energy efficiency, and electricity consumption in New Zealand,” *Energy Res. Soc. Sci.*, vol. 44, no. September 2017, pp. 178–186, 2018.