Relationship between education and households' electricity-saving behaviours in South Africa: A multilevel logistic analysis

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Relationship between education and households' electricity-saving behaviour in South Africa: A multilevel logistic analysis

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Abstract

This paper investigates the relationship between the education level of household heads and households' energy-saving practices at the micro-level in South Africa. It uses the community survey of 2016 as data source. Multilevel logistic models are estimated to account for heterogeneity that characterises the sample data due to the fact that households are nested within municipalities. The findings point to a significant and positive relationship between education level of household heads and households' energy-saving practices. Based on these results, one can infer that a household whose head is educated is more likely to have light bulbs, switch off lights in the house when not in use, and switch off appliances at the wall (not with remotes) when not in use than household whose heads have no education. Therefore, education offers a tool to incentivise households to save electricity, which will also contribute indirectly to the effort of addressing the challenges of climate change, amongst others.

Keywords: households, electricity-saving, education, municipal, South Africa

JEL classification : C31, D21, R21, Q4

1 Introduction

End-user electricity efficiency is one of many levers that can be used to achieve sustainable development, particularly in South Africa, given that

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electricity is the main energy product used by industries, mining and households. It is also worth noting that 90 percent of South Africa's electricity is generated through coal, which is one of the biggest carbon emitters. The responsibility lies with the government to ensure that there is a reduction in carbon emissions by promoting, amongst others, household electricity-saving practices. The reality is that, when households or other sectors of the economy resort to saving electricity, especially during periods when they do not need it, there will be enough capacity to supply other sectors that require it at that particular time. This will occur without necessarily needing to generate additional capacity, unless the saved capacity is less than what is required by other sectors.

The consequences of households not saving electricity when it is not needed are twofold. First, households end up paying for electricity that they do not really consume or use for useful needs, whereas they have competing needs that they must satisfy with limited financial resources. Saving electricity when it is not needed potentially could result in these households consuming other goods or services without necessarily needing additional financial resources. Second, when electricity is not saved, it means that there is a supply of a good that is not used and, most importantly, of which the production has a negative impact on the environment through carbon emission. This paper seeks to answer the question whether a household whose head is educated is more likely to save electricity than a household of which the head as no education.

However, in a country in which the black majority was deprived of access to essential services, including electricity, the government faces a challenge of finding a balance between increasing household access to electricity, and at the same time promoting energy efficiency to reduce carbon emission. As early as 1998, in the White Paper on Energy (Republic of South Africa, 1998), the government recognised the need for this balance, although promoting energy efficiency on the supply side was emphasised. In addition, the government promulgated a carbon tax law in 2019, in which it recognises that there is a need for a combination of tools and measures to address the challenges of climate change because of the multifaceted nature of this phenomenon. It is on this basis that the government ought to also promote end-user electricity efficiency, given that South Africa's economy relies heavily on electricity. This is evident in the fact that, in 2005, the government for the first time published the National Energy Efficiency Strategy (Republic of South Africa, 2005), which lays out guidelines and implementation plans for energy efficiency in all sectors of the economy in South Africa. In this strategy, the emphasis is put on the benefits of energy efficiency, as well as factors that may have delayed sectors, including households, in using energy in an efficient way. Among factors that have delayed energy efficiency is the low prices of electricity and coal in South Africa. It is in the same spirit that this paper argues that households' electricity-saving practices can be considered as measures that contribute to the mitigation of the impact of climate change, and as incentives to free households from financial pressure due to high electricity costs. For instance, Abrahamse and Steg (2009) assert that households contribute about 20 percent of total energy-related CO_2 emissions in developed countries. This situation could even be worse for a developing country such as South Africa, which relies on electricity as the main source of energy.

In view of the above, the objective of this paper is to model and explain relationships between households' electricity-saving practices and the education level of household heads in South Africa. The paper hypothesises that educated individuals are predisposed to comprehending the benefits of saving electricity for themselves and for society in general. As a result of this predisposition, rational, educated individuals are expected to adopt some behaviour to save electricity, including saving electricity in the households in which they have control. I use the recently published community survey (Statistics South Africa, 2016) as a primary source for gathering data on the outcomes and explanatory variables. It is worth recognising that there are many factors that potentially are related to households' electricity-saving practices.

Previous studies on the topic have considered factors ranging from socioeconomic and demographics to dwelling typologies to examine households' electricity-saving practices. But, given that sustainable development is now the buzzword because of climate change, the environmental dimension predominates in empirical works. For instance, Zhang, Yu, Wang and Wei (2018) point out that previous studies have considered, amongst others, environmental awareness to explain households' energy-saving practices.[1] Similarly, Martinsson, Lundqvist and Sundström (2011) focus on the relative importance of environmental attitudes to understand energy-saving behaviour in Swedish households. It can be deduced from the above that it is important for a sound study to include factors that capture households' environmental awareness.

Although it is the first time that questions on electricity-saving practices were included and collected at the household level in South Africa, the 2016 Community Survey has some limitations. For instance, it did not collect any information related directly to household environmental attitudes or awareness. Instead, this present paper uses the education level of household heads

[1] I use energy-saving and electricity-saving interchangeably throughout this paper.

because it is an important tool that government can use to promote the behaviour of electricity users, in particular households, for the benefit of society. To the best of my knowledge, it is the first time that a study assesses the relationship between education and electricity saving in households at the micro-level involving a large sample such as the 2016 Community Survey, which covers the whole of South Africa.

Another contribution of this paper resides in the methodology employed. The paper specifies and estimates multilevel logistic models. These models are often used to account for the heterogeneity that characterises the dependent variables that follow the Bernoulli distributions and are clustered to ensure reliable estimates. Data on households' electricity-saving practices used in the analysis are at the micro-level, but grouped into municipalities. In other words, they are individual households' electricity-saving practices nested in municipalities. This clustering of households' characteristics into municipalities often leads to non-randomness or dependence in the data. Thus, one has to use a multilevel modelling approach.

The structure of this paper is as follows. A discussion of previous studies on the topic and how they are related to the present paper is presented in section two, and the methodology and data are discussed in section three. Section four presents a discussion of the empirical findings. The concluding remarks are presented in section five.

2 Previous empirical studies

It is important to note that the discussion set out in this section is not restricted to electricity, but considers the energy sector as a whole. This is because electricity is a major component of energy, in particular at the residential level. As pointed out by Trotta (2018), it is now more than three decades that researchers have sought to understand the determinants of households' energy consumption and/or saving. It is important to note that a variety of perspectives and approaches are put forward in this quest. For instance, some studies focus on households' decisions to invest in energy-efficient solutions (e.g. buying energy-efficient household appliances), whereas households' energy-saving behaviour is the main interest of other studies. It is worth noting, however, that there are other studies, including that of Gram-Hanssen (2013), which focus on both aspects. However, the latter group of studies are closely related to the present paper. Thus, the discussion in the brief review set out in this section is limited to studies whose main interest is households' energy-saving practices. Zhang *et al.* (2018) present a comprehensive review of studies on the topic, which this paper recommends to interested readers.

Abrahamse and Steg (2009) examine the relationship between socio- demographic and psychological factors and households' energy use/saving. Their study is based on data from a survey conducted in the city of Groningen in the Netherlands. These authors find households' energy use is determined by socio-demographic factors, and norm-activation factors (i.e. awareness, attitude, etc.) are related to households' energy-saving practices.

Pothitou, Hanna and Chalvatzis (2016) find a positive association between environmental values, knowledge and attitudes, and households' energy-saving practices in a part of the city of Peterborough in England. These authors use a combination of tools, including principal component analysis (PCA), to analyse data collected from a survey of 249 households in the study region. Although they do not investigate the possibility of a direct link between education and households' energy-saving practices, the fact that they find a positive relationship between knowledge about energy and households' energy saving means that one can deduce that there is an indirect link between the latter and education. This is because, as stated throughout this paper, educated individuals have a cognitive capacity to understand energy and environmental matters. In the same vein, Mills and Schleich (2012) and Poortinga, Steg and Vlek (2004) suggest that there is a relationship between education and households' energy-saving practices. In addition, Mills and Schleich (2012) find a divide across European countries regarding the impact of education on households' energy-saving behaviour. These authors explain that these differences are mainly due to disparities in education structures.

Although Zhao, Cheng, Zhao, Jiang and Xue (2019) did not focus on households, their study is worth mentioning as they looked at energy-saving behaviour among students, who constitute an important segment of users assumed to be aware of the environmental effects of electricity use. They found a positive relationship between awareness and students' electricity-saving behaviour. While it is important to understand the energy-saving behaviour of different residential segments, including students, it is important to note that data used in the present study does not permit this, as it is not segmented by household users. However, this is a possibility for further research using primary data.

Yue, Long and Chen (2013) and Li, Liu, Wang and Liu (2017) have considered, amongst others, characteristics representing situational factors as determinants of energy saving. These two studies highlight the importance of situational factors, which the present paper does not consider because of a limitation in the data at hand. In addition, Liu, Wang, Wei, Chi, Ma and Jian (2020) included psychological characteristics in their analysis of energy-saving behaviour. Although the 2016 Community Survey (Statistics South

Africa, 2016) includes some characteristics that certain studies have considered as determinants of energy saving, it is important to note it contains enough information necessary for the analysis.

Moreover, the literature is rich, as it sheds light on determinants of energy saving among residents in both urban and rural settings. To name but a few, Han and Cudjoe (2020) focused on urban residents in Myanmar, whereas Zhao *et al.* (2019b) studied households' energy-saving behaviour in rural China. The former found that the degree of concern is significantly related to residents' energy saving in urban settings of Myanmar. Zhao *et al.*'s (2019b) findings indicate that rural households in China pay attention to energy conservation.

Yun and Steemers (2011) studied the factors that influence the energy-saving behaviour of urban households in China's province of Jiangsu. After conducting a survey to collect information on 638 households and carrying out the analysis, these authors find that the highest level of education in the study region has a significant impact on two types of energy-saving practices. Although their focus was on the role of government measures, Hong, She, Wang and Dora (2019) found that psychological and sociodemographic conditions are significant determinants of households' electricity-saving behaviour in China.

In contrast, studies such as those by Curtis, Simpson-Housley and Drever (1984), Sardianou (2007) and Trotta (2018) find that there is no relationship between education and households' electricity-saving behaviour. The lack of consensus among studies regarding the relationship between education and households' energy-saving practices can partly be explained by differences in estimation methods used. Also, as clearly pointed out by Mills and Schleich (2012), it can be concluded that the observed differences between studies regarding the relationship between education and households' energy-saving behaviour can be explained partly by differences in education structures or systems. This also means that the association between the two characteristics differs from case to case because countries are different.

From the survey undertaken by Lopes, Antunes and Martins (2012) it is clear that the literature on energy behaviour, which includes electricity use and conservation behaviour, is very vast and mainly focuses on the residential sector. These authors stress that the main purpose of this literature is finding determinants of electricity use and saving, which are important in the formulation of effective policies that seek to address environmental challenges. Yue *et al.* (2013) used data for 638 households in the Chinese province of Jiangsu to establish the determinants of energy-saving without considering any possibility of social interactions between households and/or influence of neighbours on household energy-saving behaviour. Similarly, Wang, Zhang and Li (2014) collected data on 276 residents in Beijing to examine characteristics that determine their energy-saving behaviour. These authors did not consider social interactions or networks and proximity interactions between these residents, which may explain the variability of their energy-saving behaviour. Although Wang *et al.* (2014) conclude that educational background is not related to household energy-saving behaviour, it is important to note that there could be a model misspecification, in particular if there are social or proximity interactions between households.

However, studies such as those by Ek and Söderholm (2010) and Hori, Kondo, Nogata and Ben (2013) are amongst the few that have considered characteristics representing social interactions as determinants of households energy-saving behaviour. Both these studies confirm that social interactions affect energy-saving behaviour. These studies rely on measurable variables to determine social interaction or networking, whereas the present paper does not have access to such variables to be considered in the analysis. Thus, this paper uses the geographical location of municipalities (i.e. polygons) to determine the proximity of municipalities, then tests whether households' electricity-saving behaviour in nearby municipalities are affected in the same way.

The point of demarcation between previous studies and the present paper is in the employment of a large sample of data covering more than half a million households to analyse the relationship between education and households' energy-saving practices. It is the first time that a study of such magnitude is applied using the South African experience. In addition, this paper uses multilevel logistic regression models to account for heterogeneity due to the hierarchical structure of the data. From a methodological perspective, the study by Belaid and Garcia (2016) is closely related to the present paper. In the mentioned study, the authors investigate the determinants of households' electricity-saving behaviour in France using microdata. The next section sets out the methodology used to model and explain the relationships between education and households' energy-saving practices.

3 Methodology

3.1 Rationale for using multilevel logistic modelling

This paper uses a multilevel logistic method to estimate the relationship between households' electricity-saving practices and the education level of household heads. The reason for using this method is twofold. First, one takes advantage of the richness of the data in the 2016 Community Survey published by Statistics South Africa (2016). This dataset is the largest survey in South Africa and contains information on the electricity-saving behaviour of more than half a million households . In addition, the targeted outcome variables, which are households' electricity-saving practices, are recorded as binary variables to indicate whether a household saves electricity or not. This suggests that the outcome variables follow Bernoulli distributions, which necessitates that a logistic regression be considered.

Second, the 2016 Community Survey presents households that are nested in municipalities and provinces in South Africa. The hierarchical nature of such data requires one to carefully consider the issue of independence in the distribution of the error terms, as it is always assumed in a single-level model specification. Furthermore, the publication of information on households' income and other important information (e.g. employment status) that was collected during the 2016 Community Survey is yet to be published by Statistics South Africa. As further discussed in the following sections, it has been established in the literature that household income is an important determinant of electricity saving. Because this information is not yet available in the dataset, this paper uses, as a way of circumventing this challenge, household income variables from the 2011 Census (Statistics South Africa, 2011), which is aggregated at the municipal level. The aggregation is justified because one cannot link individual households in the 2016 Community Survey and those from the 2011 Census. This new variable is considered as a level 2 variable, which is used together with other variables at the household level to specify and estimate multilevel logistic regressions on households' electricity-saving practices. In summary and in simple terms, the reason for considering a multilevel logistic model is mainly because of the dependent variables, which follow the Bernoulli distributions, the hierarchical structure of the data and the inclusion of a level 2 variable (i.e. aggregated household income), as explained above.

In essence, a multilevel specification is useful in disentangling and estimating two sources of variability in the behaviour of the phenomenon under investigation (i.e. households' electricity saving). Because the data is clustered, one can, on one hand, estimate the within-municipality variability of households' electricity saving within a multilevel modelling framework. This type of variability can be translated into the variability that is expected, regardless of whether or not households belong to a particular municipality. On the other hand, with a multilevel specification, it is possible to estimate a between-municipality variability of the phenomenon of interest. The between-municipality variation is an important ingredient brought to the fore by a multilevel specification. It is important because it offers an opportunity for one to examine whether, for instance, households belonging to a municipality behave in a similar manner as far as electricity saving is concerned, and behave differently compared to households belonging to other municipalities. In addition, if the proportion of between-municipality variability is important in explaining the overall variability of the phenomenon under investigation, using a single-level instead of a multilevel logistic specification will lead to inefficient and inconsistent estimates (Hox, Moerbeek and Van de Scoot, 2017).

Now that one important feature of a multilevel specification has been discussed, it is possible to bring this method into the context of regional science, where it is established that phenomena or objects belonging to a geographical area (i.e. municipality) are expected to behave in a similar manner. It has been suggested that this similarity of behaviour is mainly because of geographical, area-specific but unobserved factors that influence the phenomenon under investigation. Thus, another advantage of using a multilevel logistic specification resides in the fact that one can account for municipalities' specific factors that are represented by the random effects part in the model.

3.2 Multilevel logistic modelling procedure

This section starts by setting the scene for ease of interpretation of the equations and symbols used in the specifications. First, households are indexed by $i(i = 1, \ldots N)$, while municipalities are symbolised by $j(j = 1, \ldots S)$. In addition, three dependent variables are used alternatively in the estimation of households' electricity-saving practices. As discussed in section 3.1, each dependent variable is a binary that is equal to one if a household saves electricity ($Y_{ij} = 1$), and zero if it does not ($Y_{ij} = 0$) . Taking the logistic transformation means one is predicting the probability of a household falling into a target group, which is saving electricity. This is represented by $Prob(Y_{ij} = 1)$.

Instead of using the probabilities, which are bound to 0 and 1, the logit, which is the transformation of the predicted probability of target group membership is often used in logistic regression. The main reason for using the logit is to ensure that the relationship between the independent variables and the probability of a household saving electricity is linear. In this respect, Equation (1) below represents the logit transformation of the probability that a household saves electricity, in which $logit(p_{ij})$ stands for the log-odds of a *household* i in a *municipality* j saving electricity.

$$logit(p_{ij}) = logit(Y_{it} = 1) = \ln(odds = Y_{ij} = 1) = \ln(\frac{Prob(Y_{ij} = 1)}{Prob(Y_{ij} = 0)} \quad (1)$$

After setting the scene, now it is time to present the specification. It is worth noting that the estimation of a multilevel logistic model is procedural in the sense that it involves multiple steps. This paper follows three steps in the estimation of the multilevel logistic models, as set out below. In each step, the models are estimated with the maximum likelihood estimator (see Hox *et al.*, 2017 for details regarding the mathematical formulae).

Step 1: Null logistic models

Equation (2) below is the null multilevel logistic model.

$$\begin{aligned} logit(p_{ij}) &= \alpha_{ij} + u_j \\ u_j &\sim N(0, \sigma_u^2), \end{aligned} \tag{2}$$

where α_{ij} is the overall intercept of log-odds of a household saving electricity across all municipalities, whereas u_j is the intercept specific for a *municipality j*. Equation (2) is an unconditional specification that allows modelling the between-municipalities variation of log-odds of a household saving electricity. There are two components in Equation (2), notably the fixed-effects (α_{ij}) and the random-effects components (u_j). With regard to the latter, it is rather its variance (σ_u^2) that is estimated, as it conveys useful information for the purpose of analysis.

Furthermore, Equation (2) is used to test whether the between- municipalities variance is indeed in proportion to the within-municipalities variance and is big enough to explain the log-odds of a household saving electricity. In this respect, after estimating Equation (2), one has to calculate the interclass correlation coefficient (ICC), also known as variance partition coefficients (VPC). An ICC indicates the relative magnitude of the between-municipalities variance component. In other words, it quantifies the degree of homogeneity regarding the log-odds of a household saving electricity. Equation (3) below is the formula for calculating ICC from the estimated null multilevel logistic model.

$$\begin{aligned} ICC &= \frac{\sigma_u^2}{\sigma_u^2 + (\frac{\pi^3}{3})} \\ 0 &\leq ICC \leq 1, \end{aligned} \tag{3}$$

where $(\pi^3/3) \approx 3.29$ is the standard logistic distribution of the level 1 variance component. A higher value of ICI implies there is homogeneity or dependence between households within municipalities, whereas a lower ICC shows independence. This paper uses the conventional threshold of 0.05 to determine whether the between-municipalities variance is significant or not (Heck, Thomas and Tabata, 2014). In other words, if the estimated ICC is equal to or greater than 0.05, this paper concludes that a multilevel logistic model is necessary and proceeds to the second step set out below.

Step 2: Random intercept logistic models

After confirming the suitability of multilevel over single-level logistic models, I estimate a random intercept logistic model with respect to each dependent variable. Equation (4) below represents the specification of a random intercept logistic model considered in this paper.

$$\begin{aligned} logit(p_{ij}) &= \alpha_{ij} + \sum\nolimits_{k=1}^{K} \beta_k x_{k,ij} + u_j \\ u_j &\sim N(0, \sigma_u^2), \end{aligned} \tag{4}$$

where the meaning of terms remains the same as in Equation (2), except for the vector of K independent variables (x_{ij}), with their associated vector of K slopes (β). Equation (4) predicts the log-odds that a *household i* in a *municipality j* saves electricity as a function of the overall intercept (α_{ij}), selected independent variables that include the education level of household heads as variable of interest, and the municipalities' random effects (u_j). In other words, this model allows the intercept to vary between municipalities. For instance, the intercept of the log-odds that a household in a specific municipality saves electricity is: $\alpha_{ij} + u_j$. As in Equation (2), it is the variance (σ_u^2) that is estimated.

The main purpose of considering Equation (4) is to test against Equation (5), the discussion of which is set out below, using the likelihood ratio test (LR). The null hypothesis of the LR test is that Equation (5) is not statistically different from Equation (4).

Step 3: Random slopes logistic models

Equation (5) is referred to as the random slopes logistic models. This paper allows only the slopes of independent variables to vary between municipalities. This is because of the computational challenges involved in the estimation of full random slopes logistic models for 557 889 observations and 234 municipalities.

$$
\begin{aligned}
logit(p_{ij}) = \alpha_{ij} + \sum\nolimits_{r=1}^{R} \beta_r w_{r,ij} + \delta v_{ij} + \gamma z_{ij} + u_{1j} \\
+u_{2j} v_{ij} + u_{3j} \gamma_{ij} \\
u_{1j} \sim N(0, \sigma^2_{u_1}) \\
u_{2j} \sim N(0, \sigma^2_{u_2}) \\
u_{3j} \sim N(0, \sigma^2_{u_3}),
\end{aligned} \tag{5}
$$

where the meaning of terms remains the same as in Equation (4). However, for ease of presentation, independent variables are separated into two groups. The first group comprises variables of which slopes are not allowed to vary between municipalities. These are represented by R vectors of (w_{ij}). The second group includes two independent variables for which the slopes are allowed to vary between municipalities (i.e. age of the household head and household size). These are represented by the vectors (v_{ij}) and (z_{ij}), respectively.

Moreover, Equation (5) has fixed and random effects. The fixed-effects component is represented by $(\alpha_{ij} + \sum_{r=1}^{R} \beta_r w_{r,ij} + \delta v_{ij} + \gamma z_{ij})$. It includes the intercept and the slopes that are applicable to all households, regardless of the municipalities in which they belong. The random-effects component of Equation (4) is represented by $(u_{1j} + u_{2j} v_{ij} + u_{3j} \gamma_{ij})$, which is the intercept and the slopes for two independent variables. In this regards, one can say, for instance, that the influence of the variable v (or z) on the log-odds that a household in a *municipality* j saves electricity, all other things remaining constant, is equal to: $\delta + u_{2j}$ (or $\gamma + u_{3j}$). The same as for Equations (2) and (4), the focus is on the estimated variances of the random effects, represented by $\sigma^2_{u_1}$, $\sigma^2_{u_2}$ and $\sigma^2_{u_3}$.

3.3 Data

Table 1 below shows the variables used to estimates the models discussed in section 3.2. As already discussed in the previous section, these variables are sourced from the 2016 Community Survey (Statistics South Africa, 2016) and are considered as level 1, because they are related to households. However, the variable "*household income*" is considered a level 2 variable (related to municipalities) and is sourced from the 2011 Census (Statistics South Africa, 2011).

Before discussing the variables in greater detail, it is necessary to provide some general explanation of the data. First, of the 984 627 households surveyed, 557 889 (or 57 percent) indicated that they had access to electricity. It is these 557 889 households that are considered in the present paper. Second, although the variables related to households are from the 2016 Community Survey, this paper considers the 2011 municipal boundaries. Consequently, the 557 889 households are nested 234 local and metropolitan municipalities as they were prior to the 2016 boundaries. It is also important to note that the 2016 Community Survey is published with this grouping of households in municipalities already done by Statistics South Africa.

Third, given that a single-stage sampling design was used in the 2016 Community Survey, all variables are weighted using the household weights provided as part of the data to ensure that the estimates are not spurious.

Table 2 shows key summary unweighted statistics of the three continuous predictors used in the analysis. These statistics convey some information worth noting. First, there are disparities among households in terms of the age of the heads and the number of individual living in these households. This can be seen by the large standard deviations. Second, the reported 12 years as the minimum age of households heads is an indication that there are some child-headed households in South Africa. Although this is not the concern of the present paper, it is an important aspect that warrants further research for shedding some light on the issue. Third, 41 percent of households in a municipality on average did not have an annual income in 2011. Loosely speaking, it shows that the average level of income poverty is high in South Africa. This paper uses standardised instead of absolute continuous predictors to avoid the effects of outliers in the estimation of models, as discussed in section 3.2.

The summary of categorical variables is provided in Table 3 below. The first column of this table shows a variable, whereas the second depicts categories associated with the variable. The reference categories are shown in bold font. The number of households that fall within each category is shown in column three, and the fourth shows the same information in percent. For instance, one can read the second row of Table 4, which is related to the variable "*Light bulbs*", as follows: 478 820 out of 557 889 households with access to electricity use light bulbs. This represents 86 percent. It also means that 14 percent, or 79 069, households with access to electricity do not have light bulbs.

Dependent variables were selected to ensure variability in the sample. For instance, the reported reference categories of the dependent variables (i.e. *Light bulbs*, *switch off lights* and *switch off appliances*) in column four are greater than 5, but less than 95 percent. In terms of gender, one can note an equal split, as 50 percent of heads are females and males respectively. The majority of households heads were not married (viz. 55 percent). Most households in the sample have formal dwellings. However, there are a significant number of households that reside in backyard dwellings.

About 60 percent of household heads in the sample have not completed secondary education (that is 12 percent for *no schooling*, 14 percent for *primary 1*, three percent for *primary 2* and 32 percent for *secondary 2*). Given that secondary education is considered a basic level of education required, this finding is an indication that more effort is required to educate masses of South Africans. In addition, only 11 percent of household heads in the sample had *post-secondary* education.

Table 4 below reports the tests of independence between each of the three dependent variables and education. As it can be seen, the reported Chi-squared statistics are statistically significant at one percent level. This means that the null hypothesis of independence or no relationship between a dependent variable and education is rejected in favour of the alternative hypothesis. In other words, results in Table 4 point out that there is a strong relationship between each of the dependent variables considered in this paper and the education level of household heads. It is important to note that the main aim of the Chi-squared statistic is to simply get an overall view of the relationships between the dependent variables and education, which is the predictor of interest in the present paper. Section four discusses in details the nature and direction of these relationships.

Turning now to what this paper expects of the relationships between the independent variables and the dependent variables. First, the choice of the independent variables is determined by the literature and the availability of data. Second, starting with the variable of interest for this paper, which is the " *Education level*" of the household heads, it is expected that education would be positively related to households' electricity-saving practices. In other words, the households whose heads have a certain level of education are more likely to save electricity than households that have heads with no schooling. This is because one assumes, on the one hand, that education predisposes people to be susceptible to comprehending the benefits that can be accrued for their households from saving electricity . For instance, income gained from saving electricity could be redirected to other uses in the household. On the other hand, it is assumed that educated individuals know the benefits of saving electricity for society in general. For instance, by not using electricity when it is not needed, it means that there will be enough capacity to supply other sectors that require it at that particular time, which will contribute to the functioning of the economy. In other words, unless the saved capacity is less than what is required by other sectors, households saving electricity means there will be no need for generating additional capacity, which occurs at the expense of the environment - given that coal is the major source for electricity generation in South Africa.

The above-discussed a priori expectation of the relation between education and electricity-saving behaviour stems from the literature as the present paper has already alluded to. For instance, Borozan (2018) states that education is among key variables employed in energy studies to determine the relationship between human capital, through increased knowledge and energy-saving/consumption behaviour. Similarly, Hori et al. (2013) maintain that there is a positive relationship between education and energy-saving behaviour. This is because people with high level of education are more likely to have high level of income, through employment, which consequently makes it possible for them to undertake energy-saving investment (i.e. purchasing light bulbs)

Third, it is intuitive to expect a positive relationship between the standardised " *Age*" of household heads and the log-odd of saving electricity. This is because older heads are predisposed to understanding the benefits of saving electricity. Studies such as Boardman (2004) and Wang et al. (2011) have also considered age as a determinant of energy-saving behaviour. These studies argue that young people are less likely than older persons. With respect to " *Household size*", it is important to note that households with many members will find it difficult to practise electricity-saving measures. In other words, the more members there are in a household, the more difficult it would be for those households to control the efficient use of electricity. Thus, it is expected that there will be a negative relationship between the log-odds of a household saving electricity and " *Household size*". With regard to the proportion of " *Household income*", one expects this to be positively related to households' electricity-saving practices. This is because a rational household will use electricity sparingly, in particular when it is not needed, to minimise the costs, as it does not receive any formal annual income.

Four, characteristics such as " *Marital status*" and " *Gender*" of household heads are often included in the analysis to understand and/or measure their impact on households' electricity-saving practices. The expectation is that each of these households whose heads are married would be positively related to households' electricity saving. Simply put, it is presumed that households with married household heads are stable and organised. Similarly, households headed by females are presumed to be organised. Therefore, such behaviour will lead to them using electricity efficiently. The discussion about the expected relationship between each of the variables set out above is based on these studies Poortinga et al. (2004); Trotta (2018a); Abrahamse and Steg (2009) and Martinsson et al. (2011) , to name but a few.

Categories of the variable " *Dwelling*" are included in the analysis to capture the typologies of household dwellings. Previous studies, including those by Jones, Fuertes and Lomas (2015) and Kavousian, Rajagopal and

Fischer (2013), have examined the relationships between types of dwellings and electricity consumption and found some relationships. Although previous studies looked at electricity consumption, I believe that it is still relevant to consider these variables when one examines electricity saving. This is because electricity consumption and electricity saving are two sides of one coin.

It is worth noting a limitation of this study since it does not consider electricity price or tariff as a predictor of households' electricity-saving behaviour. For instance, studies such as Scarpa and Willis (2010), Banfi et al. (2008), Wang et al. (2011), and Dianshu et al. (2010) have considered the relationship between energy/electricity and price. These studies argue that there is a positive relationship between price and electricity-saving behaviour. The present paper does not include because there is not reliable and publicly available information that one should consider. For instance, municipalities are in terms of the law required to submit all budget documents and information to the national and respective provincial departments of treasury, which on their turn publish this information. However, it is noticed that the schedules that contains electricity tariffs are always incomplete rendering this information unusable for the type of analysis carried out in this paper. The same applies to Eskom, which is the national utility responsible to the generation, transmission and to some extent distribution of electricity. There is no publicly available information with respect to Eskom' electricity tariffs to households applicable in each area.

4 Findings

Table 5 reports only the estimates of random slopes logistic models because of space restrictions. However, key statistics related to the null and random intercept models are also reported because they are used in the diagnostic. Models 1 to 3 refer to the random slopes models for which the log-odds are that a household uses light bulbs, switches off lights and switches off appliances respectively are the dependent variables.

Before discussing the estimates in Table 5, it is important that one establishes whether there is a need for multilevel logistic models as opposed to single-level logistic models. In this respect, the reported ICCs that are calculated from the estimated null logistic models, as discussed in section 3.2, are used. It is noted that these ICCs are above the set threshold of 0.05. For instance, the ICC for Model 1 is 0.092, indicating that nine percent of the variance in the log-odds of a household having light bulbs can be attributed to differences between municipalities. Similarly, 10 percent and eight percent of variance in the log-odds of a household switching off lights and appliances respectively is due to differences between municipalities. Based on these results, it can be concluded that the data is suitable for multilevel logistic models. The next step, after confirming that multilevel logistic models are suitable, consists of determining whether random slopes models are suitable as opposed to random intercept models. This diagnostic is realised using the reported "LR test vs. random intercept model:χ^2 in Table 5. It can be seen that, for all three models, the reported χ^2 are statistically significant are the one percent level. This is an indication that the null hypothesis stipulating that random slopes models are not significant can be rejected. Thus, the random slopes models are reported in Table 5.

Table 5 also shows the variances of the three random effects, notably variance of the random intercept, and variances of the random slopes of age and household size, respectively. It can be seen that the variance of the random intercept is bigger than that of the random slopes combined. Turning now to the interpretation of the random slopes models. With respect to the fixed-effects estimate of " *Household head age*", which is statistically significant for all three models, one can say that, for an increase of one year in the age of a household head, the expected change in log odds of a household having light bulbs, switching off lights, and switching off appliances are 0.1337, 0.1054 and 0.089, respectively across all municipalities, all other things being equal. In other words, households with older heads are more likely to save electricity. It can be noted that this interpretation is straightforward as far as the magnitude of the effect is concerned. A better way to interpret estimates, in particular with regard to their magnitude, is to take the exponential of coefficient. For instance, the exponential of 0.1337 is equal to 1.1430 for Model 1.

Then, it can be said that it is expected that there will be a 13 percent increase in the odds of households having light bulbs for an increase in the age of a household head by one year across all municipalities. Similarly, a one-year increase in the age of a household head corresponds to an 11 percent (i.e. exponential (0.1054) = 1.1111) and nine percent (i.e. exponential (0.089) = 1.0930) increase in the odds of a household switching off lights when not in use and switching off appliance at the walls, respectively across all municipalities.

Table 5 also shows that the fixed effects estimates for " *Household size*" in Models 1 and 2 are statistically significant and negative. This implies that there is less likelihood of a household with many members saving electricity, all other things being constant. For instance, an increase by one member in a household corresponds with a decrease in the odds of the household having light bulbs and switching off lights by four percent (i.e. exponential (-0.0439) = 0.0957). These findings correspond with the assumption set out in this paper that one could expect a negative relationship between household size and households' electricity-saving practices.

However, the fixed effects estimate of " *Household size*" in Model 3 is counterintuitive because it indicates that there is more likelihood that households with many members will switch off appliances. Similarly, it is noted that the estimates for household income are negative, which is an indication that a household belonging to municipalities with a large proportion of households with no annual income is less likely to save electricity. As discussed in section 3.4, this is counterintuitive, as one would expect that the lack of income would influence the household to save electricity. With respect to the gender of the household heads, the results show that a household with a female head is less likely to switch off lights and appliances when not in use. This finding is also in contradiction with the assumption set forth in this paper, namely that households with female heads are better organised to an extent that they would be expected to save electricity.

Furthermore, the estimates related to the marital status of household heads confirm the assumption made in this paper. As can be seen, these coefficients are significant and negative for all three models. This is an indication that household heads who are not married are less likely to save electricity, all things being constant. The reported significant and positive estimates related to the categories " *Flat*" and " *Formal*" suggest that households living in flats and formal dwellings, respectively are more likely to save electricity than those living in backyards. However, there is less likelihood that a household living in an informal settlement will save electricity. This finding is interesting, particularly in the case of South Africa, where there are regular reports in the media of illegal electricity connections in informal settlements. Illegal connection to the electricity grid is tantamount to these households using electricity for free. Thus, there is less incentive to save electricity. While there is no evidence to back up this claim, one can interpret it with caution.

Speaking of the phenomenon of interest in this paper, the results in Table 5 show that all five categories of the variable " *Education level*" are indeed significant at the one percent level and positively related to households' electricity-saving practices. This indicates that households whose heads have an education (i.e. *Primary 1* or *Post-secondary*) are more likely to save electricity than households whose heads have no education, all else being equal. In addition, it can be noted that the estimates of " *Post-secondary*" are large in Models 1 and 2, whereas in the case of Model 3 the coefficient of " *Secondary 2*" is the largest. If one has to compare these coefficients with those for " *Primary 1*" and " *Primary 2*", it can be said that the effect of a head with post-secondary education attainment is five times (i.e. 0.7864 : 0.17101) and 18 times (i.e. 0.8364: 0.0477) that of a head having an incomplete primary education in Models 1 and 2, while in Model 3, the effect of a head with a completed secondary education is twice that of having an incomplete primary education (i.e. *Primary 1*).

As already discussed in section one of this paper, there is a presumption that educated individuals are predisposed to understanding the benefits of saving electricity. This leads them to adopt or influence their households to adopt behaviour that seek to save electricity. These behaviour may contribute, amongst others, to the minimisation of the effects of electricity consumption on the environment. Based on this finding, it can be concluded that education must be considered as a pathway or policy tool to encourage households to save electricity. This will also indirectly contribute to the government effort to address the issue of climate change.

5 Concluding remarks

This paper is pertinent because it examines households' electricity-saving practices, given that these are behaviour that contribute positively to the global agenda of reducing the impact of human activity on the environment. It uses data for 557 889 out of 984 627 surveyed households covering all 234 local and metropolitan municipalities in South Africa. The data itself was sourced from the 2016 Community Survey, which for the first time included questions related to households' electricity-saving practices (Statistics South Africa, 2016). Because of the hierarchical structure of the data, amongst others, this paper adopted a multilevel logistic modelling approach to account for the heterogeneity or similarities in electricity-saving behaviour of households belonging to the same municipalities. It was found, through a rigorous diagnostic process, that random slopes logistic models indeed were appropriate for the data. The paper was an attempt to respond to the question whether a household whose head is educated is more likely to save electricity than a household with a head who has no schooling.

The empirical findings show that, in general, the variable of interest, which is the level of education of household heads, is positively related to the odds of a household saving electricity across municipalities in South Africa. For policy purposes, it therefore is important that education, in conjunction with other tools, be considered as a lever that can accelerate end-user energy efficiency in South Africa. It was also noted that, on average, close to 60 percent of households in South Africa are headed by individuals without a completed secondary education. This implies that there is an urgent need to accelerate policies or measures that aim to increase the number of individuals with at least secondary-level education in South Africa.

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Table 1: Description of variables

Variable	Description
Dependent	
Light bulbs	A binary variable. It is equal to one (target) if a household agrees that they use energy-saving light bulbs, otherwise it is zero.
Switch off lights	A binary variable. It is equal to one (target) if a household agrees that they switch off lights when not in use, except security lights, otherwise it is zero.
Switch off appliances	A binary variable. It is equal to one (target) if a household agrees that they switch off appliances at the wall (not remote control) when not in use, otherwise it is zero.
Independent	
Household head age	Number of completed years of the household head at the time of the survey.
Household size	Number of individuals living de facto in the household at the time of the survey.
Household income	The proportion of households with no annual income in a municipality based on Census 2011.
Gender	A binary variable representing the gender of the household head. It is equal to one (reference) if the household head is a female, and zero if the head is a male.
Marital status	A binary variable representing the marital status of the household head. It is equal to one (reference) if the household head is legally married or living together as husband and wife, and zero if the head is not married.
Education level	A categorical variable indicating the completed education level of a household head. The categories are: 1. No schooling (reference) 2. Not completed primary education (Primary 1) 3. Completed primary education, or Grade 7 (Primary 2) 4. Not completed secondary education or equivalent (Secondary 1) 5. Completed secondary education, or Grade 12 or equivalent (i.e. N4) (Secondary 2) 6. Post-secondary education (Post-secondary)
Dwelling	A categorical variable indicating the main dwelling that the household currently lives in. The categories are: 1. Backyard dwelling (Backyard) (reference) 2. Formal dwelling (Formal) 3. Traditional dwelling (Traditional) 4. Flat dwelling (Flat) 5. Informal dwelling (Informal)

Table 2: Summary of continuous variables

Variable	Mean	Max	Min	STD
Household head age	47.9	116	12	16.3
Household size	3.2	40	1	2.2
Household income	41	48	27	3

Table 3: Summary of categorical variables

Variable	Category	Number of households	Percentage
Light bulbs			
	Has light bulbs = 1	478 820	86
	Does not have light bulbs = 0	79 069	14
Switch off lights			
	Switches off lights = 1	458 254	82
	Does not switch off lights = 0	99 635	18
Switch off appliances			
	Switches off appliances = 1	494 113	89
	Does not switch off appliances = 0	63 776	11
Gender			
	Female	277 286	50
	Male	280 603	50
Marital status			
	Married	249 879	45
	Not married	308 010	55
Education level			
	No schooling	64 458	12
	Primary 1	79 098	14
	Primary 2	28 105	5
	Secondary 1	179 051	32
	Secondary 2	146 985	26
	Post-secondary	60 192	11
Dwelling			
	Backyard	59 271	11
	Formal	401 055	72
	Traditional	45 446	8
	Flat	29 443	5
	Informal	22 674	4

Table 4: Statistical test of association

Relationship	Pearson's χ^2	Number of observations
Light bulbs and Education	2679.9*** (0.000)	557889
Switch off lights and Education	4090*** (0.000)	557889
Switch off appliances and Education	1239.9*** (0.000)	557889

*Figures in brackets are the p-values associated and *** refers to significance at the 1 percent.*

Table 5: Estimates of multilevel logistic models

	Dependent variable		
Parameter	**Model 1**	**Model 2**	**Model 3**
Constant	1.2859***	1.0411***	1.7305***
	(0.000)	(0.000)	(0.000)
Household head age	0.1337***	0.1054***	0.0891***
	(0.000)	(0.000)	(0.000)
Household size	-0.0439***	-0.0424***	0.1027***
	(0.000)	(0.000)	(0.000)
Household income	-0.0714**	-0.0969***	-0.0523*
	(0.010)	(0.000)	(0.054)
Gender			
Female	0.0117	-0.0164**	-0.0525***
	(0.1799)	(0.0424)	(0.000)
Marital status			
Not married	-0.1151***	-0.1358***	-0.0969***
	(0.000)	(0.000)	(0.000)
Education level			
Primary 1	0.1710***	0.0477***	0.2264***
	(0.000)	(0.000)	(0.000)
Primary 2	0.2477***	0.1209***	0.3213***
	(0.000)	(0.000)	(0.000)
Secondary 1	0.3737***	0.2460***	0.4122***
	(0.000)	(0.000)	(0.000)
Secondary 2	0.5578***	0.4660***	0.4729***
	(0.000)	(0.000)	(0.000)
Post-secondary	0.7864***	0.8364***	0.2877***
	(0.000)	(0.000)	(0.000)
Dwelling			
Traditional	-0.0292	0.0930***	-0.2209***
	(0.1790)	(0.000)	(0.000)
Flat	0.2084***	0.5037***	0.0944***
	(0.000)	(0.000)	(0.000)
Informal	-0.0291	-0.0427**	-0.1162***
	(0.1591)	(0.023)	(0.000)
Formal	0.2853***	0.3430***	0.1172***
	(0.000)	(0.000)	(0.000)
ICC	0.092	0.107	0.084
Level 2 variance at intercept	0.2997	0.3524	0.2852
Level 2 variance for Age	0.0075	0.0083	0.0063
Level 2 variance for Size	0.0069	0.0101	0.0162
LR test vs. random intercept model: χ^2	305.9***	371.18***	440.59***
Log likelihood	-210612.7	-237768.6	-189958.7
Number of groups (Level 2)	234	234	234
Number of observations (Level 1)	557 889	557 889	557 889

**, ** and * refer to significance at the 1 percent, 5 percent and 10 percent level, respectively. p-values are in parenthesis.*

Source: Author's own estimations