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A model-based clustering approach for analyzing energy-related financial literacy and its determinants*

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Abstract

Recent research highlights the role of consumer's energy-related financial literacy in adoption of energy efficient household appliances in order to reduce the energy-efficiency gap within the household sector. The computation of an indicator for such a literacy measure has followed a somewhat less refined approach though. This paper demonstrates the use of a model-based clustering strategy in order to differentiate the population based on the level of energy-related financial literacy. Using a Swiss data with $6,722$ respondents, we are able to identify three latent groups that represent low, mid and high levels of literacy. We use this new measure within an ordered logit setting with the goal of explaining the determinants of the level of energy-related financial literacy and compare empirical results using classical indicators and approaches. The empirical findings suggest a significant gender-gap among the Swiss population, i.e. females, even those with university education, are less likely to possess a high level of energy-related financial literacy. Individuals who display strong concern for free-riding on their own energy reduction behavior, are also found to have higher odds of belonging to the low literacy group. The results show that it is possible to identify latent classes that have a general and intuitive meaning and provides support to the model-based clustering approach as a sophisticated alternative. This could be a useful approach when empirical researchers are interested in (attribute-based) latent groups of consumers. The identification of latent classes also provides a possibility to target consumers belonging to these classes with specific policy measures in order to increase their level of literacy.

JEL Classification: C38, D12, D80, Q40

Keywords: Model-based clustering; Cluster analysis; Latent class; Energy-related financial literacy; Gender gap; Switzerland

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1 Introduction

The end-use efficiency at the household level depends largely upon whether or not households adopt an energy-efficient alternative when they want to purchase a new appliance. A more energy-efficient appliance usually has a higher upfront cost than a conventional one, with its benefits materializing only in the future when one takes into account the total cost (purchase price and annual energy costs) over the lifetime of the appliance. It is argued that households and individuals need to possess a certain level of energy-related financial literacy (ERFL hereafter), i.e. both energy-related knowledge and cognitive skills to process available information in purchase situation, in order to make rational energy-related investment decisions (Blasch et al., 2017b, 2018a).

In practice, such a literacy measure is usually captured in a survey setting using a questionnaire with several questions on different aspects of energy-related knowledge and skills, e.g., if a person knows the average price of electricity; knows how many units of electricity an appliance consumes; can compare electricity consumption across several appliances; is aware of the monetary cost towards consumption of typical home appliances (Blasch et al., 2017b). The standard approach, following the completion of the questionnaire by all respondents, is to count the total number of correct responses and use it to construct a score of literacy which then serves as variable in an empirical analysis. Some empirical studies have utilized such simple indicators, e.g., Blasch et al. (2018a); DeWaters and Powers (2011). We argue that it is over-simplistic to assume that all such questions have the same importance towards a measure of an individual's ERFL. Nonetheless, one question that has largely remained overlooked is - what is a good way to combine the correct responses to the numerous literacy related survey questions into a single measure, either to compare two respondents (e.g., via a score), or to classify respondents in different groups depending on their level of literacy?

An index of ERFL can be used for descriptive statistical analysis, i.e. to give an overall picture of the level of literacy in a geographical region. On the other hand, this index could also be used as dependent variable in a regression analysis. In this case, the researcher is interested in analyzing the determinants of ERFL. It is important to examine the socio-economic determinants of ERFL, given its crucial role in decision-making in the domain of energy-related consumption and appliance adoption. Blasch et al. (2018a) provide an excellent overview of the findings related to the role of gender in household decision-making. In general, past studies have found a persistent gender gap in the context of (financial) decision making (Almenberg and Dreber, 2015; Lusardi and Mitchell, 2014). In the context of energy-related decisions though, there is limited research and the role of gender is still unclear. There is, however, some evidence that females play a crucial role in purchase decisions on major household appliances, e.g., Belch and Willis (2002) report that the change in family structure over the past decades have impacted the family decision making process and that female (spouses) have gained more influence in the household-decision making process. Moreover, Albert and Escardíbul (2017) find that education of both spouses have a positive effect on the decision process when both partners take joint household decisions.

Given the above motivation, this paper makes one primary contribution towards the literature. As an alternative strategy to using simple indices to capture the level of ERFL, this study demonstrates the use of a refined model-based clustering approach to distinguish underlying groups, or latent classes, of individuals belonging to similar levels of ERFL. We find that the model is able to identify three latent classes that appear to represent LOW, MID, and HIGH levels of ERFL. The obtained latent classes are then used as a dependent variable in an ordered logit framework to explain the determinants using a rich set of socio-economic attributes. The results are compared with those obtained with dependent variables constructed using classical aggregation approaches. The analysis is based on a Swiss household survey data of $6,722$ households. The paper shows that it is possible to identify literacy based latent classes that are reasonable and more intuitive to understand, and the approach does not make simplistic assumptions related to aggregation or weights in order to construct an index.

Moreover, unlike the classical approaches, the number of classes following a clustering strategy is not affected directly by the number of multiple choice (quiz-style) questions in a survey.

This study has three main objectives – (1) to present an alternative sophisticated strategy to measure the ERFL; (2) to use this new measure within a classical setting with the goal of explaining the determinants of the level of ERFL; and (3) to compare empirical results with classical indicators and approaches.

The results show that it is possible to identify latent classes that have a general and intuitive meaning and provides support to the model-based clustering approach as a sophisticated alternative. The empirical findings suggest a significant gender-gap among the Swiss population, i.e. females, even those with university education, are less likely to possess a high level of energy-related financial literacy. Individuals who display strong concern for free-riding on their own energy reduction behavior, are also found to have higher odds of belonging to the low literacy group.

The remaining sections are organized as follows. Section 2 provides a brief background on the energy-related financial literacy measure, discusses some issues with the present approach of constructing literacy indicators, and presents some of the existing clustering methods. Section 3 summarizes the dataset used and presents the empirical strategy. Section 4 reports the results and Section 5 concludes.

2 Literature review

2.1 Energy-related financial literacy and its indicators

In a recent work, Blasch et al. (2018a) review several definitions and concepts related to energy literacy and financial literacy in the existing literature, e.g., DeWaters and Powers (2011); Brounen et al. (2013); Kalmi et al. (2017). They also propose a new concept of 'energy-related financial literacy' which encompasses both energy-related knowledge and cognitive skills to process available information in order to take informed energy-related investment decisions. Formally, Blasch et al. (2018a, p. 3) define energy-related financial literacy as the "combination of energy-related knowledge and cognitive abilities that are needed in order to take decisions with respect to the investment for the production of energy services and their consumption".

The above mentioned studies take different approaches in constructing an indicator for literacy for the purpose of exploratory and econometric analysis. Blasch et al. (2018a) sum-up all the correct responses (1 point for correct, 0 otherwise) and construct several combinations of literacy indicators. DeWaters and Powers (2011) set up several questions distributed over three sub-scales - cognitive, affective and behavioural, and then sum-up the scores to obtain an indicator for each sub-scale. Brounen et al. (2013), on the other hand, consider six different constructs that describe energy awareness and literacy, and have one question that captures each construct. They use the response to these questions to estimate six different logit and regression models for the different constructs. Kalmi et al. (2017), using a Finnish household data, consider a binary variable for energy literacy which equals one when respondents correctly answer each of the two questions meant to capture energy literacy. Similarly, a binary financial literacy indicator equals one if all the three questions meant to capture financial literacy are answered correctly. Another binary indicator that is related to awareness of different operating costs equals one when respondents correctly answer at least two out of three questions.

As mentioned earlier in the introduction, the current research tends to rely on less refined and rather simple approaches to quantify the level of literacy. They either aggregate the number of correct responses (Blasch et al., 2018a; DeWaters and Powers, 2011), use a somewhat simplistic weighting technique (Blasch et al., 2017b), or identify some or all questions to be important and take a combination of the scores as representative (Kalmi et al., 2017).

Below we describe how the construction of a literacy indicator sometime inadvertently presupposes some strong assumptions. Consider that you are measuring the level of literacy via a survey questionnaire that consists of several multiple choice quiz-style questions. Each question has one correct answer. Several respondents take part in your survey, and on completion of the survey, you have a matrix of ones (correct answer) and zeros (incorrect answer). The objective then is to come up with an easy method to quantify and compare the level of literacy across your sample.[1]

If you were interested in ranking, you might be interested in obtaining an overall numeric score or a grade. One obvious way to achieve this is to count all the correct responses and sum up. This approach, though, is arguably too simple – it assumes that each question has the same importance and that the sum total represents the underlying literacy. The latter point depends directly on the number of questions, and adding another question to the survey would simply add another variable. If you want to give different weights to different questions, how do you decide on the weights, as no underlying established theory is available to base your assumptions on.

In order to avoid the problem of weighting, one could think of another approach. Instead of trying to find a literacy score for each individual, an alternative could instead be to classify them into different literacy based (latent) groups. The foremost questions would then be, given the responses to the survey question on literacy, how to classify respondents into different groups; what is the number of latent groups that one should choose; and, after the classification, how to interpret the meaning of the different groups. While more number of groups may help better separate the respondents, it would likely render the interpretation of the groups difficult.

In the next section, we look at some strategies that could be of help when our goal is to classify observations into latent groups.

2.2 Classification approaches

Classification and clustering approaches tend to fall into two broad categories - supervised learning and unsupervised learning. Supervised learning refers to cases when one works with a multivariate data consisting of a *known* number of groups and the main goal is to classify new observations into one of these groups, e.g., a bank that wants to predict whether a prospective consumer would default on a loan.[2] On the other hand, unsupervised learning pertains to situations when there are no known prior group labels, and the goal is to examine if there are groups or clusters of observations in the data that are homogeneous and separated from the other groups, e.g., a search engine that clusters similar images or text documents on the internet, or a marketing company interested in finding groups of customers with similar behavior.

In the context of our household level data, we assume that there exists latent groups of individuals based on their level of energy-related financial literacy but we do not know the group labels beforehand.[3]

[1] In order to define ERFL, the main challenges concerns with the selection of the appropriate questions and aggregation of the correct answers.

[2] In statistics, supervised learning cases link to discriminant analysis. A classical textbook example is the Tibetan skull data from Morant (1923). 32 skulls, belonging to two groups of people, were discovered by an archaeologist. Measurements were taken on five different dimensions of the skull. The contextual question here was – if another skull is uncovered and whose origin is unknown – to which of the two groups would the new skull be classified into, based on the same five measurements taken on the skulls.

[3] One might also look at the literacy measure as a continuous latent attribute that is captured via several questions, i.e. observed variables, in a survey. A factor analysis approach, which aims at explaining correlations among the observed variables, is sometimes employed in such cases though they were traditionally designed for continuous (and in some cases, likert-type rating) variables (Everitt, 2005). Their application with binary observed variables is highly debatable,

Hence, we focus here on unsupervised learning methods, also collectively referred as cluster analysis, and provide a brief insight into some of the common methods following Everitt (2005); Everitt and Dunn (2001); Gordon (1999).

The general goal of cluster analysis is to find groups in a multivariate dataset, so that elements within cluster are very similar and elements between clusters are very different. Three main methods are usually discussed: i) Hierarchical clustering; ii) Partitioning methods, e.g., K-means clustering; and iii) Model-based clustering.

2.2.1 Hierarchical clustering

With hierarchical (or agglomerative) clustering, the idea is to build up clusters starting from individual observations. Each observation is considered a cluster to start with and the strategy involves joining clusters that are closest until only one cluster is left. Two clusters are joined based on a chosen dissimilarity criterion (e.g., euclidean or manhattan distance) and the output is similar to an evolutionary tree (Everitt, 2005). Consequently, hierarchical classification methods have mostly been found suitable for biological applications. Everitt (2005) summarizes the strategy in the following steps:

1. Start with clusters $C_1, C_2, \ldots, C_n$ each containing a single observation.
2. Find the nearest pair of distinct clusters, say C_i and C_j. Merge C_i and C_j, i.e. $C_i \cup C_j = C_i$, then delete C_j and decrease the number of clusters by one.
3. If the number of remaining clusters equals one then stop, else go to step 2.

Illustrations of this approach can be found in Everitt and Dunn (2001) and Everitt (2005). Although an agglomerative approach can get solutions for all possible number of clusters at once, they tend to be slow.[4] Observations which are grouped together at some point in the algorithm cannot be separated anymore. Furthermore, the approach is considered exploratory in nature as there is no underlying model.

2.2.2 Partitioning methods (K-means clustering)

In partitioning methods like K-means, the number of clusters are fixed in advance. The basic idea here is to start with a set of cluster centres and then assign each observation to the centre closest to it (using some numeric criterion or distance measure). The cluster centre is then recomputed such that it results in the greatest improvement of the numeric criterion, e.g., one that minimizes the within-group sum of squares. This approach is continued in a recurring way until no move of one observation from one cluster to another results in further improvement of the numeric criterion (Everitt, 2005). The basic steps in this algorithm are summarized by Everitt (2005) as:

1. Start with some initial partition of the observations into the required number of clusters.
2. Calculate the change produced in the clustering criterion by *moving* each observation from its own cluster to another cluster.
3. Make the change that leads to the greatest improvement in the value of the clustering criterion.

but has still been explored, e.g. in Kamata and Bauer (2008), assuming an underlying continuous variable within a binary observed variable.

[4] One can obtain different number of clusters by cutting the tree at a certain height. The number of clusters are usual chosen at the point where the largest vertical drop in the tree is seen.

4. Repeat steps (2) and (3) until no further move of an observation causes the clustering criterion to improve.

Illustrations of this approach can again be found in Everitt and Dunn (2001) and Everitt (2005). The K-means approach is exploratory in nature and can be really fast. As a result, this approach could be well-suited for extremely large samples. It is to be noted that the results depend on the starting values and, as in hierarchical clustering, there is no underlying formal model.

2.2.3 Model-based clustering

The model-based clustering, more generally known as a Gaussian Mixture Model (GMM), is different from the above two distance based heuristic methods for cluster analysis. It is a more formal approach that relies on a statistical model for the data generating process, and makes it possible to draw formal inferences (Everitt, 2005; Fraley and Raftery, 2002). It assumes that the population from which the sample is drawn, has several sub-populations corresponding to different clusters. The approach makes assumption (Gaussian) on underlying density of the sub-populations and involves an iterative method for maximizing the likelihood function of the observations belonging to one of the several sub-populations.

Formally, the model assumes an underlying Gaussian Mixture Model for K populations with different probability distributions (Fraley and Raftery, 2002) and is represented as:

$$f(x;p,\theta) = \sum_{j=1}^{K} p_j\, g_j(x;\theta_j) \tag{1}$$

where p_j is the mixture weight or probability of cluster j, θ_j represents the distribution parameters, and g_j is the density function for the jth population. The number of classes K, and parameters p_j and θ_j are found given the data. Observation x is assigned to cluster j, where estimated value of $P(cluster\ j|x) = \dfrac{p_j\, g_j(x;\theta_j)}{f(x;p,\theta)}$ is the largest. Fitting a GMM is typically done via a maximum likelihood approach.[5]

Some of the main challenges of GMM include the choice of the number of clusters, giving meaning to the clusters (which could generally be hard), and that for large samples, GMM can quickly becomes memory intensive.[6] The choice of number of clusters entails a trade-off between model fit and model complexity. Increasing the number of clusters would, even if only slightly, always provide a better separation of the clusters. At the same time, more clusters imply difficulty in their interpretation.[7]

In empirical research, there are only a few studies that have employed versatile approaches such as the ones described above. For instance, linear discriminant analysis and factor analysis approaches have been used, e.g., in finance (Awh and Waters, 1974), sociology (McKennell, 1970) and applied economics (Nunes, 2002; Below et al., 2012; Kim et al., 2014). For classification problems, the literature has barely scratched the surface with only a few examples that have used exploratory methods like K-means clustering (Dudeni-Tlhone et al., 2013; Max Bittel et al., 2017).

There is very little research in applied economics that make use of model-based clustering approaches. One recent application is seen in Csereklyei et al. (2017) who use this method to detect the typical

[5] In practice, a large number of samples and clusters can quickly become a hard optimization problem. In multivariate analysis, a simplification is to restrict the covariance matrices to certain patterns, e.g., spherical, diagonal and ellipsoidal (Everitt, 2005).

[6] For 10^n sample, GMM involves covariance matrices with 10^{2n} entries.

[7] A recommended approach for deciding the number of clusters makes use of a maximal BIC criterion that penalizes the number of parameters resulting from each additional clusters (Everitt, 2005).

inter-temporal development of the energy mixes of member states of the European Union using a rich panel dataset over 1971 - 2010. Some studies within the benchmarking and efficiency analysis literature have also made use of latent class based approaches, e.g., to compare cost efficiency in the electricity distribution sector (Cullmann, 2012; Agrell et al., 2014) and in banking (Orea and Kumbhakar, 2004). These studies use a latent class strategy to account for the underlying firm-heterogeneity with respect to production technology. In applied energy economics using dis-aggregate household level data - to the best of our knowledge - this perhaps is the first study demonstrating the use of a model-based clustering strategy.

3 Data and methodology

3.1 Dataset

The data used for the empirical analysis comes from a large household survey on energy use in Switzerland.[8] The survey and the underlying dataset has been discussed in many recent publications (Blasch et al., 2017a,b,c) and extensive details of the survey can be found in Blasch et al. (2018b, Ch. 2). In summary, the online survey asked more than 8,000 respondents across Switzerland about their socio-economics and dwelling related attributes, energy-related literacy, financial literacy, attitudes and household behaviours towards energy consumption and conservation. In this study, we use a sub-sample of 6,722 respondents who were asked the literacy related questions in their version of the survey questionnaire.[9]

Table 1 reports the names, description, and the summary statistics of all the variables in our dataset. The sample consists of 39% females and respondents are distributed across different age-groups and income classes. The sample has a high share of university educated respondents (40%).[10]

Table 2 reports the summary statistics for all the quiz-style knowledge questions related to energy-related financial literacy (questions are shown in the Appendix). Two questions tested if respondents knew the usage cost of running a desktop PC for 1 hour (*kn_pcuse*) and a washing machine cycle (*kn_wmuse*). We notice that people, in general, do not perform well in these questions. Three pairwise comparison questions checked if respondents, given two energy services, knew which consumes more electricity, e.g., running a desktop PC versus a laptop for 1 hour (*kn_pair3*). Respondents are found to perform well on these pairwise comparison questions – more than 50% get these correct. One question tested if people knew the average price of electricity in Switzerland (*kn_kwh*) and only one in four respondents answered correctly. One question on financial literacy checked if respondents could perform compound interest (*compound*). Swiss respondents performed well on this question and about 2/3rd get it correct.

It is worth noting that construction of a literacy related index, or a literacy based category, of course depends upon the inputs, i.e. the number and types of questions. One of the shortcomings of this dataset, compared, e.g., to Blasch et al. (2018a), is that the financial aspect of the literacy indicator is captured by just one compound interest question. Lusardi and Mitchell (2008, 2014) proposes that a measure of financial literacy comprises three aspects (i) capacity to do interest calculation, (ii) understanding the difference between nominal and real values (i.e. effect of inflation),

[8] The survey was conducted by the Centre for Energy Policy and Economics (CEPE), ETH Zurich in collaboration with several Swiss electrical and gas utilities.

[9] A total of nine Swiss utilities partnered with us. Two utility partners opted to have a shorter questionnaire and decided not to include some questions including the literacy related questions.

[10] Blasch et al. (2018b) provides a discussion on the representativeness of the survey dataset by comparing it with available national and city level statistics. Note that a high share of university educated respondents does not necessarily undermines the conclusions drawn in this paper since the sample size is quite large and university education is not the only criterion that is expected to define the underlying ERFL.

Table 1: Descriptive statistics of the survey sample.

		Statistic			
Description	*Variable*	*Mean*	*Std.Dev.*	*Min.*	*Max.*
Respondent is female	*female*	0.39	0.49	0	1
Age group of respondent					
below 40	*age40m*	0.26	0.44	0	1
40 to 60	*age40_60*	0.40	0.49	0	1
above 60	*age_60plus*	0.34	0.47	0	1
Monthly household income					
below 6,000 CHF	*hhi6k*	0.32	0.47	0	1
6,000 to 12,000 CHF	*hhi6_12k*	0.50	0.50	0	1
more than 12,000 CHF	*hhi12k*	0.18	0.38	0	1
University education	*univ*	0.40	0.49	0	1
Spouse has university education	*univ_partnr*	0.19	0.39	0	1
Owned residence	*is_owner*	0.45	0.50	0	1
Single family house	*is_sfh*	0.33	0.47	0	1
Minergie certified building	*minergie*	0.09	0.28	0	1
Language					
German	*languageDE*	0.65	0.48	0	1
French	*languageFR*	0.05	0.21	0	1
Italian	*languageIT*	0.29	0.45	0	1
English	*languageEN*	0.01	0.11	0	1
Pro-environmental attitude	*atd_moral_oblig*	0.75	0.43	0	1
Willingness to compromise	*atd_willing_compromise*	0.70	0.46	0	1
Concern for free-riding	*atd_conc_freeride*	0.09	0.28	0	1

Note: Sample refers to a total of 6,722 Swiss respondents. Categorical variables, i.e. age, income and language, are reported in terms of dummy variables for each category.

Table 2: Literacy related attributes of the survey sample.

		Statistic			
Description	*Variable*	*Mean*	*Std.Dev.*	*Min.*	*Max.*
Knows cost of using a PC	*kn_pcuse*	0.42	0.49	0	1
Knows cost of using a Washing machine	*kn_wmuse*	0.19	0.39	0	1
Correct answer to pairwise comparison Q1	*kn_pair1*	0.77	0.42	0	1
Correct answer to pairwise comparison Q2	*kn_pair2*	0.66	0.48	0	1
Correct answer to pairwise comparison Q3	*kn_pair3*	0.57	0.49	0	1
Knows the cost of 1 kWh electricity	*kn_kwh*	0.25	0.43	0	1
Knows compound interest calculation	*compound*	0.66	0.47	0	1

Note: Sample refers to a total of 6,722 Swiss respondents. All variables are dichotomous. The survey questions corresponding to these literacy variables are included in the Appendix.

and (iii) understanding the basics of risk-diversification. Our dataset does not capture the aspects on risk diversification and inflation. However, we argue that this is perhaps less of a concern for our Swiss sample in the context of energy-related financial literacy. The average annual rate of inflation in Switzerland has remained in between -0.8% to 0.8% since the year 2009 (FSO, 2018). The importance of risk-diversification has its roots in the financial planning literature and its role, if any, within the domain of energy-related literacy and appliance choice is not clearly laid out at the moment.

3.2 Methodology

Our empirical objective is to estimate the determinants of the ERFL for the large sample of Swiss households. For this, we first compute an alternative dependent variable for ERFL using the model-based clustering strategy and then compare the estimation results with those obtained using couple of classical approaches of constructing an ERFL score.

The first step comprises identification of clusters, or latent classes, of individuals who are similar based on their performance on all the literacy related questions in the survey. We achieve this by applying a model-based clustering approach described earlier in Section 2.2.3 to classify respondents in latent classes and examine whether the optimum division can be interpreted to resemble clusters with different levels of literacy. For simplicity, we consider three groups – a low-literacy group, a mid-literacy and a high-literacy group. Our interest here lies in knowing to which of the three literacy based latent classes a respondent belongs to.[11]

In the next step, we model the obtained ERFL based latent classes with an ordered response logit model in order to examine its socio-economic determinants.

3.2.1 Empirical model for explaining the difference in ERFL

After obtaining meaningful literacy based clusters of our respondents, we are interested in examining the socio-economic determinants of the difference in the level of ERFL. For this, we fit an ordered logit model to the Swiss household survey data. This is a model for the cumulative probability of the *i*th respondent falling in the *j*th ERFL cluster or below (Agresti, 2002). The model is:

$$\text{logit}(P(Y_i \leq j)) = \alpha_j - \boldsymbol{\beta}'\mathbf{X} \qquad \text{where} \quad \begin{array}{l} i = 1, \ldots, N, \\ j = 1, \ldots, J-1 \end{array} \tag{2}$$

Here, i is the index for all respondents ($N = 6,722$) and j is the index of the latent classes (J = 3 here). α_j is the threshold parameter for the jth cumulative logit. $\mathbf{X}$ represents the vector of explanatory variables and $\boldsymbol{\beta}$ represents the vector of coefficients to be estimated. Here, $\mathbf{X}$ includes several socio-economics characteristics of the respondents, such as gender, age-group, income class, education, language; and dwelling attributes, such as residence ownership status and whether the respondent lives in a single family or a multi-family household.

Note that we use three different dependent variables for estimating the ordered logit model. The first dependent variable (denoted as ERFL-cluster) is the ERFL based latent group obtained using the clustering strategy which is the primary focus of this paper. For comparison, we consider two classical approaches used in the literature to construct a ERFL score – the second dependent variable (denoted as ERFL-index7) is obtained by summing up the number of correct responses; and the third dependent variable (denoted as ERFL-index14) is constructed by taking different weights on the correct responses.[12] We then compare the results obtained using the three models with the three different dependent variables.

[11] One could assume a different number of underlying literacy based latent classes. A two cluster analysis might represent groups with a low and high level of literacy but is perhaps too simple. On the other hand, 4 or more groups quickly becomes complex and poses difficulty in interpretation of the resulting latent classes. Three groups with low, mid and high levels of literacy seems like a reasonable choice in this context. Nevertheless, Table 11 in the Appendix also reports empirical results assuming two latent classes. The results are found to be similar in substance to those presented here with three groups.

[12] ERFL-index7 and ERFL-index14 are further described in Section 4.2 when we present the results of the ordered logit model.

4 Results

In the following, we present the empirical results of the three models. Before that, we present and discuss the literacy based latent classes obtained using the model-based clustering approach. Lastly, as a robustness check, we re-estimate the empirical models in Blasch et al. (2017b,a,c) by making use of the literacy based clusters obtained here and discuss the results.

4.1 The latent classes

The classification results from the model-based clustering approach is presented below. We try to identify the meaning of the classes and then compare household attributes and individual characteristics across the obtained classes. Table 3 reports the share of correct responses towards the seven questions, which collectively measured the ERFL, across the three latent classes.[13]

Table 3: Latent classes based on the level of literacy.

	Latent classes		
Variable	*Class 1*	*Class 2*	*Class 3*
kn_pcuse	1.00	0.00	0.16
kn_wmuse	0.37	0.04	0.12
kn_pair1	0.86	0.86	0.41
kn_pair2	0.76	0.83	0.09
kn_pair3	0.70	0.69	0.08
kn_kwh	0.39	0.18	0.11
compound	0.79	0.67	0.42
Group label:	**HIGH-Literacy**	**MID-Literacy**	**LOW-Literacy**

Note: The latent classes are estimated using a model-based clustering approach with three clusters. The classes are assigned a label (last row) based on an interpretation of the differences in means of the underlying literacy questions across the three clusters. The model grouped the 6,722 respondents as – 39.1% in HIGH-Literacy, 40.7% in MID-Literacy, and 20.2% in LOW-Literacy.

In Table 3, one can clearly distinguish *Class 1* as the group of respondents with a high level of ERFL, i.e. the HIGH-Literacy group - respondents belonging to this group perform better than others on almost all the questions. The interpretation of the other two latent classes is somewhat less evident. One could, however, still identify the cluster labelled *Class 3* as a low literacy group (LOW-Literacy) that performs the worse in 5 of the 7 questions. The third group, *Class 2*, appears to perform somewhere in the middle compared to the low and high literacy clusters and is labelled as MID-Literacy.[14]

Given the three latent classes, Table 4 reports a simple comparison of means of the other exogenous variables across the literacy based latent classes. Somewhat expected difference can be observed across gender, age, income and education. Females, elderly respondents, low-income households, respondents without university education - all have a higher presence in the LOW-literacy group.

[13] The `mclust` package (Fraley et al., 2012; Fraley and Raftery, 2002) in R (R Core Team, 2017) was used to perform the model-based clustering. The best model chosen by the `mclust` package was spherical, equal volume (EII) with 3 components.

[14] A closer inspection reveals that although both the LOW and MID literacy groups were quite bad at the two questions that asked about the consumption (in monetary units) of a PC use and of a washing machine cycle, the LOW-Literacy group performs better than the MID-literacy group. On the other hand, the MID-Literacy group performed best on the questions on pairwise-comparison, marginally better than even the HIGH-Literacy group. It is interesting to note that the model-based clustering approach is able to distinguish between two different types of underlying skills, i.e. awareness of monetary consumption of individual energy services, and comparison between electricity consumption of two energy services.

In terms of dwelling attributes, respondents who live in an owned residence, or in a single family household, each have a slightly higher presence in the HIGH-literacy group. In terms of language, German speaking respondents are seen to have more presence in the HIGH-literacy group.

Table 4: Comparison of variable means across the literacy based latent classes.

	Latent classes		
Variable	*LOW-Literacy*	*MID-Literacy*	*HIGH-Literacy*
female	0.483	0.481	0.258
age40m	0.182	0.299	0.260
age40_60	0.382	0.391	0.415
age_60plus	0.436	0.310	0.324
hhi6k	0.418	0.355	0.246
hhi6_12k	0.451	0.482	0.533
hhi12k	0.131	0.164	0.221
univ	0.292	0.388	0.472
univ_partnr	0.129	0.181	0.224
is_owner	0.451	0.416	0.486
is_sfh	0.309	0.301	0.368
minergie	0.101	0.080	0.086
languageDE	0.483	0.676	0.712
languageFR	0.064	0.049	0.033
languageIT	0.439	0.264	0.244
languageEN	0.013	0.011	0.010
atd_moral_oblig	0.728	0.773	0.748
atd_willing_compromise	0.664	0.726	0.679
atd_conc_freeride	0.146	0.073	0.074

Note: Sample refers to a total of 6,722 respondents. This table reports a simple comparison of means of the other exogenous variables across the literacy based latent classes.

Table 4 reports an interesting observation with respect to attitudes related to energy conservation - a higher share of respondents who are concerned about free-riding (*atd_conc_freeride*) on their own energy reduction behaviour, tend to be part of the LOW-literacy group.[15] No significant differences can be noticed across the classes on the other two aspects, feeling morally obliged to reduce energy consumption (*atd_moral_oblig*), or willingness to make compromises on current lifestyle for the benefit of the environment (*atd_willing_compromise*).

4.2 Determinants of the level of literacy

Table 5 reports the estimation results of proportional-odds logistic regression (ordered logit) models in order to explain the determinants of the three ordered clusters of ERFL in our sample (Model (1) with ERFL-cluster as outcome). For comparison, we estimated two other ordered logit models that use (typical) aggregated literacy index score as outcome. The response variable for Model (2) is ERFL-index7 – a score between 0 and 7 obtained by summing up the number of correct responses to all literacy related questions. The response for Model (3) is ERFL-index14 which is a different weighted version of the score that lies in between 0 and 14.[16]

The coefficients reported in Table 5 represent the log odds ratio. A comparison of results across the three models shows that, broadly speaking, the signs, magnitude and significance of coefficients

[15] These are respondents who agree or strongly agree to the statement "I am not willing to reduce my energy consumption if others don't do the same."

[16] Following the strategy in Blasch et al. (2017b,a), this index score is constructed by assigning different points for correct answers to the seven literacy questions: 3 points each for *kn_pcuse*, *kn_wmuse* and *compound*; 2 points for *kn_kwh*; and 1 point each for *kn_pair1*, *kn_pair2 and kn_pair3*.

on most explanatory variables are similar. The log odds ratio in Models (2) and (3) are found to be higher than in Model (1) for most variables. A consequence of working with large number of deterministic scores as response is that it thins out the number of observations at each level of the score. Besides, the approach towards construction of such indices, as in (2) and (3), is less refined and rather simple. Our arguments from Section 2 in favor of a model-based clustering strategy again applies here.

For the remaining discussion of estimation results and marginal effects, we focus only on the results obtained from Model (1) with response as latent groups based on ERFL.[17] Note that the coefficients of the proportional odds logistic model in Table 5 are interpreted as changes in the log odds of moving from LOW literacy group to MID or HIGH groups, or from LOW or MID literacy groups to HIGH group, resulting from one unit increase of the quantity of interest, given that all other variables in the model are held constant.

Most of the coefficients are expected. The coefficient on being a female is negative and significant implying that females exhibit lower odds than males to possess a HIGH level of ERFL. With respondents younger than 40 years of age as reference, respondents older than 60 years display higher odds of falling in the lower level of literacy. The group between 40 to 60 years does not exhibit a significantly different behaviour than the reference group. Respondents living in a middle and high income household are also more likely to have a higher level of ERFL compared to those belonging to low income households. With respect to the level of education, respondents with university level education tend to have a higher ERFL.

In term of dwelling related attributes, home owners exhibit a higher level of ERFL compared to respondents who live in a rented dwelling. This is understandable as owners have the responsibility for replacement of old and broken appliances and to decide whether or not to undertake renovation measures, both of which implies that they likely have a better awareness of energy prices and consumption. Respondents living in the French and Italian speaking regions of Switzerland have a lower ERFL compared to the German speaking region.[18]

The model also includes interactions terms for gender with age, university education and language. Female with university education still show a significant negative coefficient which highlights the gender gap in the level of energy-related financial literacy.

The variable *atd_conc_freeride* is found to be significant with a strong negative value, i.e., individuals who display strong concern for free-riding on their own energy reduction behavior, also have a higher odds of belonging to the LOW-literacy group. One might argue that the cause and effect with ERFL and attitude works in an opposite manner, i.e. an individual's energy-related financial literacy shapes her attitude towards concerns for free-riding. As an additional analysis, we estimated a probit model with *atd_conc_freeride* as the binary response and the ERFL clusters as a covariate along with other socio-economic attributes. In the Appendix, we report the model estimates (Tables 12) and the marginal effects (Table 13). We observe that compared to the HIGH-literacy group, respondents belonging to the LOW-literacy group exhibit a higher probability (4.2 percentage points) of being concerned about free-riding on their energy reduction behavior.

[17]The `MASS` package (Venables and Ripley, 2002) in R was used for the ordered response analysis. Marginal effects were calculated using the `effects` (Fox, 2003; Fox and Hong, 2009) and `margins` (Leeper, 2018) packages.

[18]Surprisingly, respondents living in a minergie certified building exhibit a slightly lower odds of belonging to the higher literacy group. This could be a mere model artifact as the survey respondent may not necessarily be the person in the household who decided to move and reside in a minergie certified building.

Table 5: Estimation results of ordered logit models with different types of literacy measures.

	Dependent variable:		
	ERFL-cluster	ERFL-index7	ERFL-index14
	(1)	(2)	(3)
female	-0.754^{***}	-0.852^{***}	-0.953^{***}
	(0.109)	(0.103)	(0.102)
age 40-60	-0.092	-0.065	0.013
	(0.085)	(0.078)	(0.077)
age above 60	-0.558^{***}	-0.467^{***}	-0.308^{***}
	(0.087)	(0.080)	(0.079)
hhincome 6k-12k	0.188^{***}	0.222^{***}	0.268^{***}
	(0.056)	(0.052)	(0.052)
hhincome > 12k	0.221^{***}	0.346^{***}	0.421^{***}
	(0.079)	(0.073)	(0.072)
univ	0.428^{***}	0.567^{***}	0.577^{***}
	(0.066)	(0.061)	(0.060)
univ_partnr	0.124^{*}	0.121^{**}	0.109^{*}
	(0.067)	(0.061)	(0.060)
is_owner	0.135^{**}	0.221^{***}	0.222^{***}
	(0.062)	(0.057)	(0.056)
is_sfh	0.125^{**}	0.106^{*}	0.043
	(0.061)	(0.057)	(0.056)
minergie	-0.200^{**}	-0.118	-0.104
	(0.083)	(0.078)	(0.076)
languageFR	-0.555^{***}	-0.713^{***}	-0.676^{***}
	(0.151)	(0.144)	(0.142)
languageIT	-0.710^{***}	-1.029^{***}	-0.874^{***}
	(0.070)	(0.066)	(0.064)
languageEN	-0.338	-0.609^{**}	-0.565^{**}
	(0.304)	(0.291)	(0.280)
atd_moral_oblig	0.075	0.136^{**}	0.095^{*}
	(0.060)	(0.056)	(0.055)
atd_willing_compromise	0.053	0.078	-0.008
	(0.057)	(0.053)	(0.052)
atd_conc_freeride	-0.376^{***}	-0.376^{***}	-0.340^{***}
	(0.085)	(0.079)	(0.078)
female:age 40-60	-0.059	-0.132	-0.062
	(0.118)	(0.110)	(0.108)
female:age above 60	0.253^{**}	0.124	0.158
	(0.128)	(0.120)	(0.119)
female:univ	-0.248^{**}	-0.270^{***}	-0.241^{***}
	(0.100)	(0.093)	(0.092)
female:languageFR	-0.075	-0.119	-0.091
	(0.222)	(0.211)	(0.209)
female:languageIT	0.052	0.121	0.067
	(0.106)	(0.100)	(0.099)
female:languageEN	-0.343	0.126	0.275
	(0.445)	(0.422)	(0.407)
Threshold coefficients:			
LOW|MID	-1.787^{***}	-	-
	(0.0972)		
MID|HIGH	0.187^{*}	-	-
	(0.095)		

Note: *p<0.1; **p<0.05; ***p<0.01. Number of observations $= 6,722$. This table reports the estimation results of three ordered response logit models with response as (1) ERFL-cluster - three ordered latent classes for levels of literacy, i.e. LOW, MID and HIGH; (2) ERFL-index7 - a score varying from 0 to 7 obtained by summing up the number of correct responses to all literacy related questions; and (3) ERFL-index14 - a weighted version of the score varying from 0 to 14. The coefficients represent the log odds ratio. For sake of brevity, threshold coefficients for (2) and (3) are not reported here.

4.2.1 Marginal effects

The results presented in Table 5 can be used to make inferences and it is a common practice to look at the average marginal effects (AME) of predictors. Table 6 reports the average marginal effects of all variables across the three latent groups. A gender gap is clearly noticeable – being female instead of male additionally increases the probability of belonging to the LOW-literacy and MID-literacy group by 11.9 and 5.6 percentage points respectively, and additionally decreases the probability of belonging to the HIGH-literacy group by as much as 17.5 percentage points. Compared to below 40 years of age, being older than 60 years additionally decreases the probability of belonging to the HIGH-literacy group by 10.3 percentage points. Strong regional differences are also visible, i.e. belonging to French or Italian speaking regions, instead of a German speaking region, additionally decreases the probability of belonging to the HIGH-literacy group by 12.6 and 14.9 percentage points respectively. Similarly, we can also identify other important effects for attributes like income and university level education.

Table 6: Average marginal effects (AME) of the ordered logit model across the literacy based latent classes.

	Latent classes		
Variable	*LOW-Literacy*	*MID-Literacy*	*HIGH-Literacy*
female	0.119	0.056	-0.175
age 40-60	0.017	0.008	-0.025
age above 60	0.066	0.037	-0.103
hhincome 6k-12k	-0.029	-0.012	0.041
hhincome $>$ 12k	-0.034	-0.014	0.048
univ	-0.046	-0.028	0.074
univ_partnr	-0.019	-0.008	0.027
is_owner	-0.021	-0.009	0.030
is_sfh	-0.019	-0.008	0.027
minergie	0.030	0.013	-0.044
languageFR	0.093	0.033	-0.126
languageIT	0.111	0.038	-0.149
languageEN	0.079	0.020	-0.099
atd_moral_oblig	-0.011	-0.005	0.016
atd_willing_compromise	-0.008	-0.004	0.012
atd_conc_freeride	0.057	0.025	-0.082

Note: This table reports the average marginal effects for the ordered logit model with ERFL based latent groups as the dependent variable. The model consisted of interaction terms for gender with age, language and university education.

Another useful post-estimation inference technique is to let one or more focal predictors vary and then visualize the response changes by plotting predicted probabilities against the predictors. The resulting plots are sometimes referred to as effect displays. We focus our attention on analyzing the conjoint effects of some of the important attributes like gender, age and university education and we produce effect displays in order to visualize some of the findings.

Figure 1 shows an effect display of predicted probabilities across gender and age groups. There are six panels depicting the three latent classes (rows) for the two genders (columns). The age group is shown on the x-axis and the resulting predicted probabilities on the y-axis. In the upper right panel, we see that for females, the probability of being in the HIGH literacy group decreases with age. This is also true for males as seen in the upper left panel. Interestingly, elderly males show a sharper drop in the probability compared to elderly females. Overall, a clear gender gap and age gap is visible in belonging to the LOW and HIGH literacy groups which is less evident for the MID literacy group.[19]

[19] Note that it was expected to obtain different trajectories as the interaction coefficient on gender and age in the ordered logit model in Table 5 was found to be significant.

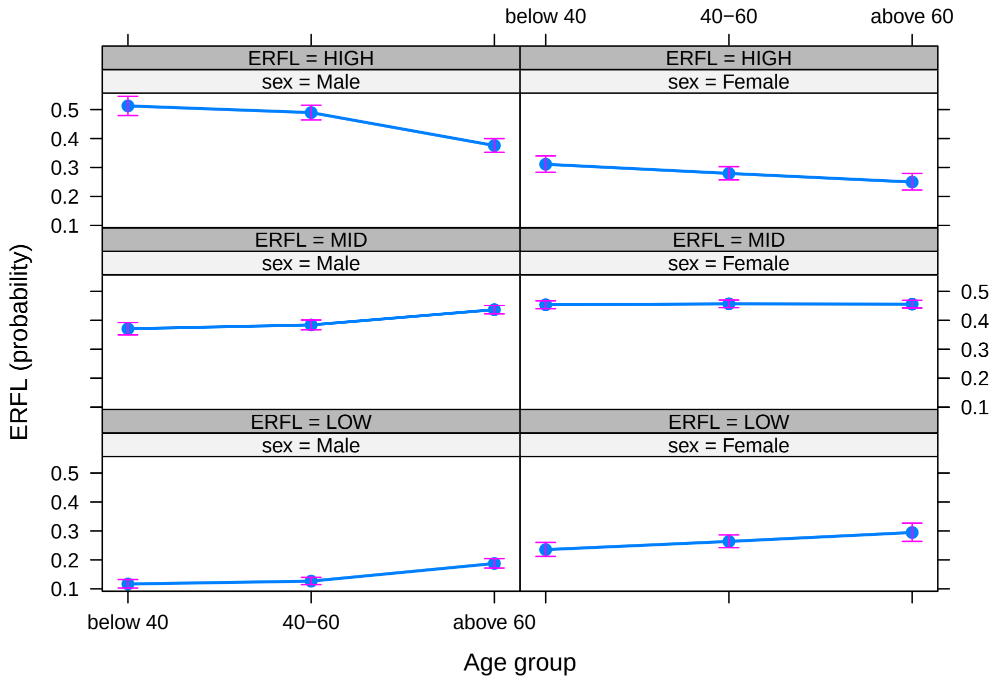
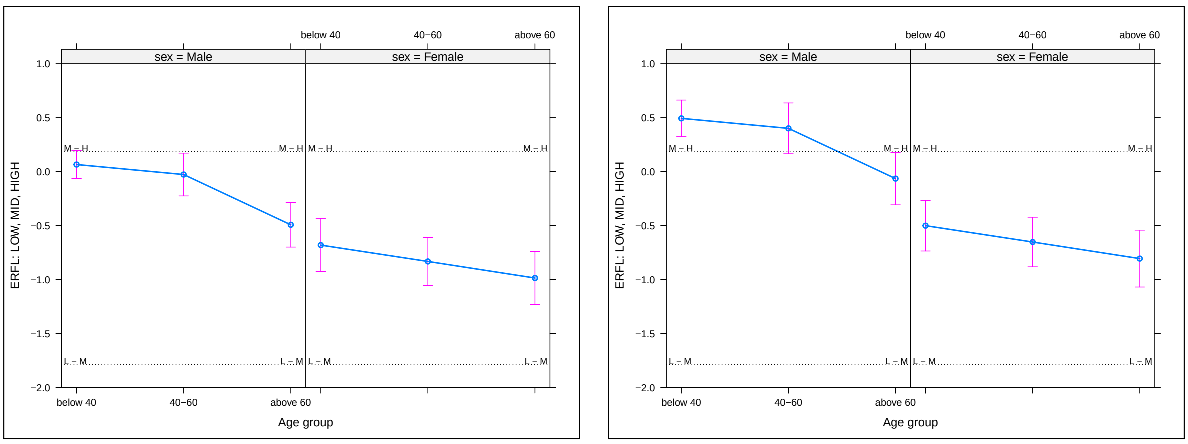


Figure 1: Effect plot of age and gender.

Figure 2 shows an effect display for the classification thresholds for gender and age interaction, first without a university education (Fig. 2a), and then with a university education (Fig. 2b). The L-M lines indicate boundary between LOW and MID literacy classes and M-H, the boundary between MID and HIGH literacy classes. The main observation is that females, irrespective of age and university education, tend to fall into the MID-literacy group. Non-elderly males with university education, on the other hand, are more likely to fall in the HIGH literacy group.



(a) Without university education (b) With university education

Figure 2: Effect plot of age and gender conditional on university education.

Figure 3 shows an effect display of predicted probabilities over the concern for free-riding on respondent's own energy reduction behaviour. As was observed earlier, it is found to be related to the literacy group – with increasing concern for free-riding, the probability of being in the LOW literacy group increases, and that of being in the HIGH literacy group decreases.

In the Appendix, we report similar effect display plots for income and gender (Figure 8) and for

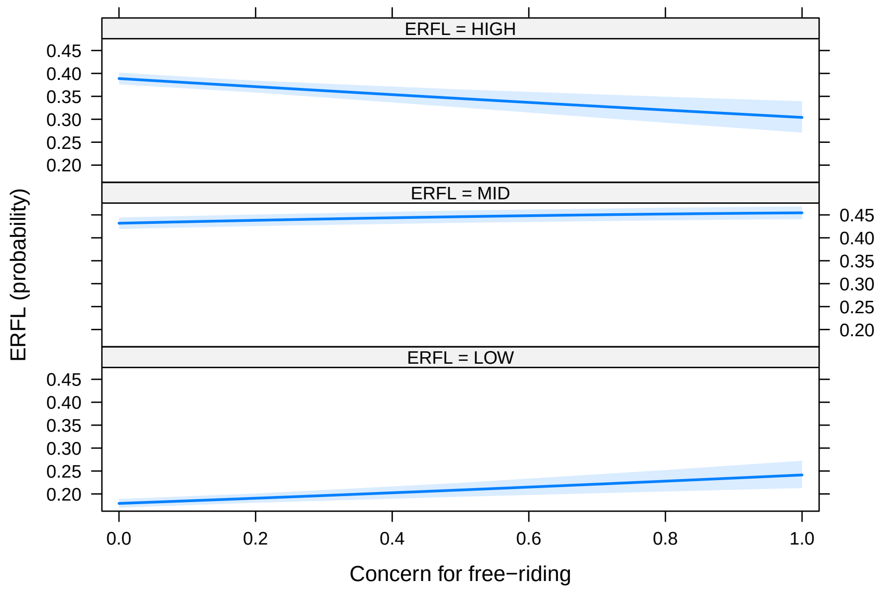


Figure 3: Effect plot of concern for free-riding.

language and gender (Figure 9). Figure 8 shows that, irrespective of the gender, belonging to high income category increases the probability to fall in the HIGH-literacy group and reduces the probability to fall in the LOW literacy group. Figure 9 shows that German speaking respondents, both men and women, tend to exhibit much higher probability to fall in the HIGH literacy group. Italian speaking respondents, on the other hand, show a higher probability of belonging to the LOW literacy group.

4.3 Robustness check of previous results using the clustering approach

In this sub-section, we re-estimate the empirical models in Blasch et al. (2017b,a,c) by making use of the literacy based clusters for ERFL obtained here instead of the less refined numeric energy literacy score and investment literacy dummy used in these studies.[20] The main goal is to compare and discuss the results across the studies using the two different approaches. Consequently, the clustering approach also serves as a robustness check for the results obtained in these studies on the role played by energy and investment literacy.

First, we consider the light bulb and refrigerator RCTs in Blasch et al. (2017b) and the HSEU-Bern RCT in Blasch et al. (2017c). We focus only on the bivariate probit (BP) and recursive bivariate probit (RBP) settings as these are the two main economic models pursued in these studies (with RBP as the preferred model). Table 7 reports the (re-)estimation results using literacy based clusters for the two experiments in Blasch et al. (2017b). Table 8 reports the (re-)estimation results using literacy based clusters for the HSEU-Bern RCT in Blasch et al. (2017c). Note that in these results, literacy is now captured using latent clusters with the LOW-literacy (i.e. variable ERFL-LOW) as reference. For the sake of completion, we also produce a combined table that reports the marginal effects using the clustering approach for all the RCT-experiments (Table 9).

Note that, due to the difference in how we account for energy and investment literacy using latent groups for ERFL, the set up of the bivariate models is now slightly different. Earlier, in the bivariate models, investment literacy was considered only in the first step outcome - the choice of investment analysis as the decision strategy. Now, following the approach with clusters based on low, mid and

[20]These studies use different subsets of the same dataset that is used here.

high levels of ERFL that uses *all* literacy questions, there is no segregation of energy and investment literacy. Consequently, the literacy based clusters are used as explanatory variables in both binary outcome equations in all the BP and RBP models.

Table 7 shows that compared to respondents belonging to the LOW-literacy group, those part of the HIGH-literacy group are more likely to perform an optimization rather than relying on a decision-making heuristic. Individuals belonging to both MID and HIGH literacy groups are also more likely to identify the appliance with the lowest lifetime cost. Displaying the information on the future energy consumption in monetary units (CHF) rather than physical units (kWh) continues to be vital for individuals to make a calculation and to identify the appliance with the lowest lifetime cost. Other attributes like gender, age and university education also exhibit similar findings to the results reported in Blasch et al. (2017b).

Table 8 finds a positive role of both MID-literacy and HIGH-literacy groups on the probability to opt for a lifetime cost calculation strategy and in turn to identify the appliance with the lowest lifetime cost. The two decision aids (TRSLIDE and TRCALC) are found to have a positive impact on the probability that an appliance with the lowest lifetime cost is chosen and, similar to the results in Blasch et al. (2017c), the calculator tool is found to be more effective than the information slides.

Table 9 reports the marginal effects of our variables of interest similar to the ones reported in the two studies. Blasch et al. (2017b) report positive impact of both energy and investment literacy which is also seen here - ERFL-HIGH cluster exhibits a higher probability to choose the appliance with the lowest lifetime cost by 4.4 percentage points in the Light bulb experiment and by 24.8 percentage points for the refrigerator experiment. In the two experiments, the marginal effects of providing the yearly energy consumption in monetary terms (TREATCHF) is about 3.3 points and 28.9 points, and that of the endogenous investment calculation decision strategy (INVCALC) is about 5.1 points and 75.3 points respectively. These findings are very similar to those reported in Blasch et al. (2017b) where the effect of TREATCHF is about 3.6 points and 29.3 points, and that for INVCALC is about 7.8 points and 77.9 points. Note that all the effects are stronger in the refrigerator experiment than the light bulb experiment. As discussed in Blasch et al. (2017b), the higher marginal effect in the refrigerator experiment is likely due to the fact that in this experiment, the most cost-efficient appliance could only be identified when comparing lifetime usage costs of both appliances, which requires some calculation. Similarly, the marginal effects in Blasch et al. (2017c) for the two decision aids, and for the choice of lifetime cost calculation strategy, are found to be very similar with the results reported in Table 9.[21]

To summarize, the main model estimation results are found to be comparable to the results reported in Blasch et al. (2017b) and Blasch et al. (2017c) that uses separate variables for energy literacy (numeric score from 0 to 11) and investment literacy (dichotomous variable) - this provides support to the clustering approach as a sophisticated alternative to less refined aggregation strategies and serves as a robustness check towards the crucial role played by energy-related financial literacy in the domain of appliance choice.

Next, we look at the stochastic frontier model for estimation of efficiency in the use of electricity in Blasch et al. (2017a). Table 10 reports the (re-)estimation results using literacy based clusters in the main generalized true random effect model (GTREM-1) for the electricity demand estimation in

[21]Note that the marginal effect of ERFL clusters are not found to be significant here. In Blasch et al. (2017c), the pre-treatment energy literacy shows a small positive impact and the investment literacy (captured by a dummy) shows a significant impact. Undertaking that the ability to perform compound interest calculation is much more important in this experiment, it is crucial to note that all the three clusters obtained here performed somewhat better in the compound interest calculation question – 42% of the LOW-literacy, 67% of the MID-literacy and 79% of the HIGH-literacy answered the compound interest question correctly. Therefore, with LOW-literacy cluster as the reference, MID and HIGH literacy groups show insignificant impacts.

Table 7: Clustering based estimation results for Blasch et al. (2017b).

	Light bulb (N=1958)		Refrigerator (N=877)	
	BP	RBP	BP	RBP
Investment calculation equation...				
Constant	-1.064***	-1.056***	-1.150***	-1.161***
	(0.143)	(0.142)	(0.208)	(0.221)
FEMALE	-0.334***	-0.339***	-0.545***	-0.553***
	(0.076)	(0.076)	(0.123)	(0.123)
AGE40_59	-0.024	-0.031	-0.151	-0.138
	(0.086)	(0.086)	(0.155)	(0.155)
AGE60P	-0.304***	-0.313***	-0.407**	-0.487***
	(0.094)	(0.094)	(0.160)	(0.164)
OWNER	0.120	0.119	-0.006	0.056
	(0.074)	(0.074)	(0.129)	(0.133)
HHI6_12K	0.117	0.118	0.214*	0.116
	(0.081)	(0.081)	(0.127)	(0.130)
HHI12K	0.233**	0.238**	0.213	0.048
	(0.109)	(0.108)	(0.180)	(0.189)
UNIEDU	0.248***	0.243***	0.131	0.356***
	(0.070)	(0.070)	(0.107)	(0.113)
ATTMORAL	-0.047	-0.044	-0.055	-0.075
	(0.079)	(0.079)	(0.122)	(0.124)
ERFL-MID	-0.014	-0.019	0.103	0.113
	(0.099)	(0.099)	(0.151)	(0.153)
ERFL-HIGH	0.346***	0.341***	0.354**	0.357**
	(0.097)	(0.097)	(0.154)	(0.154)
TREATCHF	0.346***	0.348***	0.583***	0.577***
	(0.066)	(0.066)	(0.112)	(0.113)
Appliance choice equation...				
Constant	0.962***	0.819**	-1.178***	-1.582***
	(0.212)	(0.355)	(0.218)	(0.224)
FEMALE	0.079	0.147	-0.382***	-0.026
	(0.124)	(0.181)	(0.120)	(0.131)
AGE40_59	0.075	0.084	-0.296*	-0.196
	(0.128)	(0.123)	(0.156)	(0.173)
AGE60P	0.254*	0.317*	-0.297*	-0.001
	(0.145)	(0.172)	(0.161)	(0.169)
OWNER	0.084	0.054	0.016	-0.002
	(0.122)	(0.130)	(0.127)	(0.124)
HHI6_12K	0.069	0.037	0.361***	0.197
	(0.134)	(0.139)	(0.125)	(0.133)
HHI12K	-0.054	-0.118	0.469***	0.307*
	(0.171)	(0.204)	(0.169)	(0.171)
ITALSP	0.066	0.071	—	—
	(0.134)	(0.128)		
FRENCHSP	—	—	0.005	-0.032
			(0.106)	(0.113)
ATTMORAL	0.152	0.150	-0.206*	-0.170
	(0.128)	(0.127)	(0.116)	(0.119)
ATTCONCE	0.261	0.254	0.149	0.194
	(0.250)	(0.244)	(0.194)	(0.206)
ORDEFF	-0.159	-0.151	-0.085	-0.072
	(0.112)	(0.111)	(0.099)	(0.107)
ERFL-MID	0.462***	0.441***	0.084	0.029
	(0.138)	(0.158)	(0.149)	(0.154)
ERFL-HIGH	0.395***	0.294	0.584***	0.372**
	(0.140)	(0.266)	(0.153)	(0.160)
TREATCHF	0.270**	0.184	0.680***	0.335***
	(0.111)	(0.209)	(0.108)	(0.122)
INVCALC	—	0.610	—	2.449***
		(1.025)		(0.250)
RHO(1,2)	-0.054	-0.419	0.677***	-0.704***
	(0.078)	(0.632)	(0.049)	(0.181)

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis. The table reports the (re-)estimation results using literacy based clusters in the bivariate probit (BP) and recursive bivariate probit (RBP) models for the two experiments in Blasch et al. (2017b). Literacy is captured using latent clusters with ERFL-LOW as reference.

Table 8: Clustering based estimation results for Blasch et al. (2017c).

	HSEU-Bern RCT (N=916)	
	BP	RBP
...Stage 1: Choice of lifetime cost calculation approach		
Constant	-0.441**	-0.597***
	(0.188)	(0.192)
FEMALE	-0.214**	-0.203**
	(0.094)	(0.094)
AGE40_59	-0.064	-0.014
	(0.107)	(0.107)
AGE60P	-0.124	-0.070
	(0.132)	(0.134)
OWNER	0.201*	0.202*
	(0.118)	(0.119)
HHI6_12K	0.163	0.085
	(0.102)	(0.103)
HHI12K	0.425***	0.299**
	(0.147)	(0.148)
UNIV	0.281***	0.475***
	(0.083)	(0.091)
PRO_ENV_ATTD	0.135	0.093
	(0.108)	(0.111)
ERFL-MID	0.358**	0.381***
	(0.140)	(0.142)
ERFL-HIGH	0.636***	0.627***
	(0.141)	(0.143)
TRSLIDE	0.066	0.290***
	(0.102)	(0.105)
TRCALC	-0.157	-0.070
	(0.105)	(0.105)
...Stage 2: Choice of refrigerator with the lower lifetime cost		
Constant	-0.536***	-1.499***
	(0.196)	(0.196)
FEMALE	-0.371***	-0.216*
	(0.096)	(0.112)
AGE40_59	-0.170	-0.069
	(0.105)	(0.119)
AGE60P	-0.370***	-0.264*
	(0.136)	(0.144)
OWNER	0.007	-0.142
	(0.117)	(0.118)
HHI6_12K	0.250**	0.041
	(0.106)	(0.122)
HHI12K	0.471***	0.034
	(0.140)	(0.171)
PRO_ENV_ATTD	0.000	-0.099
	(0.108)	(0.101)
ORDEFF	0.021	0.021
	(0.080)	(0.084)
ERFL-MID	0.105	-0.276*
	(0.149)	(0.152)
ERFL-HIGH	0.419***	-0.173
	(0.148)	(0.174)
TRCALC	0.230**	0.429***
	(0.093)	(0.100)
compTLC	—	2.398***
		(0.203)
RHO(1,2)	0.732***	-0.713***
	(0.036)	(0.238)

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis. The table reports the (re-)estimation results using literacy based clusters in the bivariate probit (BP) and a recursive bivariate probit (RBP) models for the HSEU-Bern RCT in Blasch et al. (2017c). Literacy is captured using latent clusters with ERFL-LOW as reference.

Table 9: Average marginal effects for the bivariate models.

	Blasch et al. (2017b)				Blasch et al. (2017c)	
	Light bulb		Refrigerator		HSEU-Bern	
	BP	*RBP*	*BP*	*RBP*	*BP*	*RBP*
ERFL-MID#	-0.003	0.048	0.028	0.038	0.068	-0.055
	(0.027)	(0.017)	(0.066)	(0.066)	(0.028)	(0.061)
ERFL-HIGH#	0.101	0.044	0.021	0.248	0.090	0.032
	(0.029)	(0.018)	(0.068)	(0.076)	(0.029)	(0.060)
INVCALC	—	0.051	—	0.753	—	0.673
		(0.001)		(0.001)		(0.002)
TREATCHF#	0.097	0.033	0.104	0.289	—	—
	(0.018)	(0.013)	(0.050)	(0.064)		
TRSLIDE#	—	—	—	—	0.015	0.049
					(0.023)	(0.026)
TRCALC#	—	—	—	—	-0.072	0.174
					(0.027)	(0.040)

Note: Robust standard errors in parenthesis. The effects are calculated at variable means. Marginal effects of exogenous variables (marked with #) are for *INVCALC=1*. In HSEU-Bern, *INVCALC* is represented as variable *compTLC*.

Blasch et al. (2017a).[22] The coefficients obtained on the different attributes are found to be very similar. With ERFL-LOW as reference, households representing MID and HIGH levels of literacy are associated with lower household electricity demand. Other household and dwelling attributes have the expected sign and most of the coefficients are similar to the results reported in Blasch et al. (2017a).[23]

The findings obtained through this exercise – employing literacy based latent clusters instead of a simple numeric score – serves as a robustness check and reinforces the insight that energy-related financial literacy plays a vital role in the domain of appliance choice, household electricity consumption, and end-use efficiency in the use of electricity. Furthermore, it provides support to the model-based clustering approach as a sophisticated alternative. The results show that it is possible to identify classes that have a general and intuitive meaning, and the approach does not make simplistic assumptions related to aggregation or weights in order to construct an index.

5 Outlook

Recent research highlights the role of consumer's energy-related financial literacy in adoption of energy efficient household appliances in order to reduce the energy-efficiency gap within the household sector. The computation of an indicator for such a literacy measure has followed a somewhat less refined approach though. This paper demonstrates the use of a model-based clustering strategy in order to differentiate the population based on the level of energy-related financial literacy. We are able to identify three groups of individual that represent low, mid and high levels of energy-related financial literacy. Further, the paper studies the socio-economic determinants of the level of literacy. The findings suggest a significant gender-gap among the Swiss population, i.e. females, even those with university education, are less likely to possess a high level of energy-related financial literacy.

[22] Recall that the dataset used is an unbalanced panel over five years (2010-2014) that consists of 8295 observations corresponding to 1994 Swiss households.

[23] Although not presented here for brevity, the persistent (22.6%) and transient (10.6%) levels of inefficiency in the use of electricity were also found to very similar to the values reported in Blasch et al. (2017a). The results suggest that improvement in the level of ERFL presents a considerable efficiency improvement potential among Swiss households.

Table 10: Clustering based estimation results for GTREM-1 in Blasch et al. (2017a).

	GTREM-1	
	Coefficient	*Std. error*
(Log) price of electricity	-0.330***	(0.037)
Single family household	0.174***	(0.007)
(Log) household size	0.333***	(0.011)
(Log) dwelling size in m^2	0.363***	(0.009)
Has young people	-0.047***	(0.008)
Has elderly people	0.036***	(0.006)
Income in 6k - 12k	-0.011*	(0.006)
Income above 12k	-0.020**	(0.009)
Built in 1940 - 1970	-0.067***	(0.008)
Built in 1970 - 2000	0.073***	(0.007)
Built in 2000 - 2015	-0.029***	(0.009)
Minergie house	-0.006	(0.010)
Absent 5 to 8 weeks/year	-0.138***	(0.009)
Has 2nd fridge	0.103***	(0.007)
Has separate freezer	0.115***	(0.005)
No special appliances	-0.080***	(0.006)
(Log) number of cooked meals	0.016**	(0.006)
(Log) dish-washing cycles	0.119***	(0.004)
(Log) cloth washing/drying cycles	0.098***	(0.004)
(Log) hours of tv/pc	0.159***	(0.004)
Cooks using electricity	0.096***	(0.008)
(Log) heating degree days	-0.039	(0.110)
(Log) cooling degree days	0.158***	(0.046)
Region = Aarau	0.021	(0.020)
Region = Winterthur	-0.106***	(0.040)
Region = Biel/Bienne	0.058**	(0.024)
Region = Lucerne	-0.070***	(0.017)
Region = Bellinzona	-0.192***	(0.066)
University degree	-0.029***	(0.006)
University degree (partner)	-0.009	(0.007)
(Log) energy saving behaviour	-0.019***	(0.007)
ERFL-MID	-0.109***	(0.007)
ERFL-HIGH	-0.090***	(0.007)
Time trend (linear)	-0.107***	(0.023)
Time trend (quadratic)	0.021***	(0.004)
α	5.477***	(0.718)
σ_w	0.395***	(0.002)
$\sigma_{(\nu+u)}$	0.254***	(0.003)
λ	0.751***	(0.043)
σ_h	0.652***	(0.018)

Note: *p<0.1; **p<0.05; ***p<0.01. The table reports the (re-)estimation results using literacy based clusters in the main generalized true random effect model (GTREM-1) for the electricity demand estimation in Blasch et al. (2017a). The dataset with 8295 observations is an unbalanced panel over five years (2010-2014) and corresponds to 1994 Swiss households. Literacy is captured using latent clusters with ERFL-LOW as reference.

Another interesting observation is that individuals who display strong concern for free-riding on their own energy reduction behavior, are also found to have higher odds of belonging to the low literacy group. We re-estimate the empirical models in Blasch et al. (2017b,a,c) by making use of the literacy based clusters for ERFL. The similarity in obtained results serve as a robustness check and reinforces the insight that energy-related financial literacy plays a vital role in the identification of the lowest lifetime cost appliance, in household electricity consumption, and in end-use efficiency in the use of electricity. Moreover, the results provide support to the model-based clustering strategy as a sophisticated alternative.

The empirical results highlight systematic gaps with respect to gender and age and indicates significant potential for improvement in the level of energy-related financial literacy for all consumers. One way to do this would be to include, e.g., as part of the general education curriculum in schools, specialized courses or training that focuses on improving this important dimension of literacy. Another way, that could be undertaken both by the utilities and the government, is to have focused information campaigns in order to create awareness among existing and new consumers, e.g., about electricity prices, about usage cost of typical energy-consuming household appliances, and to teach consumers how to calculate the lifetime cost of appliances in order that consumers are able to rationally evaluate options in purchase scenarios.

The results show that it is possible to identify latent classes that have a general and intuitive meaning, and the approach does not make simplistic assumptions related to aggregation or weights in order to construct an index. Moreover, unlike the classical approaches, the number of classes following a clustering strategy is not affected directly by the number of multiple choice (quiz-style) questions in a survey. This could be a useful approach when empirical researchers are interested in (attribute-based) latent groups of consumers. Lastly, the identification of latent classes also provides a possibility to target consumers belonging to these classes with specific policy measures in order to increase their level of literacy.

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Appendix

How much do you think it costs in terms of electricity to run:

Amount in Rappen / Centimes:	0-19	20-39	40-59	60-79	80-100	More than 100	Don't know
a desktop PC for 1 hour	○	○	○	○	○	○	○
a washing machine (load of 5 kg at 60°C)	○	○	○	○	○	○	○

Figure 4: Energy literacy questions on monetary cost of energy services.

In the following pairs, which of the two consumes more electricity?

Pair 1:

- ○ Bringing 1 litre of water to a boil in an average pot with lid
- ○ Running a washing machine with a load of 5kg at 60°C
- ○ Both consume about the same
- ○ Don't know

Pair 2:

- ○ Bringing 1 litre of water to a boil in an average pot with lid
- ○ Bringing 1 litre of water to a boil in an electric kettle
- ○ Both consume about the same
- ○ Don't know

Pair 3:

- ○ Running a desktop PC for 1 hour
- ○ Running a laptop for 1 hour
- ○ Both consume about the same
- ○ Don't know

Figure 5: Energy literacy questions on pairwise comparison of electricity consumption.

How much do you think 1 Kilowatt hour (kWh) of electricity currently costs in Switzerland (on average)?
Please indicate your best guess without checking your bill or other resources.

- Don't know
- Amount in Rappen / Centimes (no decimals)

Figure 6: Energy literacy question on the price of 1 kWh of electricity.

Let's say you have 200 CHF in a savings account. The account earns 10% interest per year.
How much would you have in the account at the end of 2 years?

- 220 CHF
- 240 CHF
- 242 CHF
- 204 CHF
- Don't know

Figure 7: Survey question on calculation of compound interest.

Table 11: Estimation results of the ordered logit model with two latent classes.

	Dependent variable:
	ERFL-cluster (2 groups)
female	-0.852^{***}
	(0.124)
age 40-60	-0.129
	(0.093)
age above 60	-0.395^{***}
	(0.094)
hhincome 6k-12k	0.267^{***}
	(0.063)
hhincome >12k	0.471^{***}
	(0.088)
univ	0.447^{***}
	(0.071)
univ_partnr	0.139^{*}
	(0.074)
is_owner	0.064
	(0.070)
is_sfh	-0.015
	(0.068)
minergie	0.023
	(0.093)
languageFR	-0.573^{***}
	(0.163)
languageIT	-0.853^{***}
	(0.075)
languageEN	0.258
	(0.351)
atd_moral_oblig	0.000
	(0.067)
atd_willing_compromise	0.077
	(0.063)
att_conc_freeride	-0.364^{***}
	(0.098)
female:age 40-60	-0.235^{*}
	(0.135)
female:age above 60	-0.011
	(0.150)
female:univ	0.077
	(0.114)
female:languageFR	-0.103
	(0.269)
female:languageIT	-0.173
	(0.132)
female:languageEN	-0.401
	(0.509)
Threshold coefficient:	
LOW|HIGH	-0.154
	(0.103)

Note: *p<0.1; **p<0.05; ***p<0.01. This table reports the estimation results of an ordered response logit model to explain the determinants of the two ordered clusters of ERFL in our sample of $6,722$ respondents. The coefficients represent the log odds ratio.

Table 12: Estimation results of the logit model with concern for free-riding behavior as outcome.

	Dependent variable:
	Concern for free-riding
ERFL-MID	0.023
	(0.108)
ERFL-LOW	0.533***
	(0.115)
female	−0.494**
	(0.234)
age 40-60	0.226
	(0.259)
age above 60	0.860***
	(0.236)
hhincome 6k-12k	0.193
	(0.225)
hhincome >12k	−0.039
	(0.343)
univ	−0.226*
	(0.121)
univ_partnr	−0.040
	(0.134)
is_owner	0.022
	(0.111)
is_sfh	−0.267**
	(0.112)
minergie	−0.060
	(0.162)
languageFR	0.570***
	(0.197)
languageIT	0.947***
	(0.096)
languageEN	0.187
	(0.472)
female:age 40-60	0.096
	(0.264)
female:age above 60	−0.055
	(0.272)
age40-60:hhincome 6k-12k	−0.296
	(0.285)
age above 60:hhincome 6k-12k	−0.715***
	(0.269)
age 40-60:hhincome >12k	0.060
	(0.397)
age above 60:hhincome >12k	0.072
	(0.393)
female:univ	−0.077
	(0.218)
Constant	−2.867***
	(0.219)

Note: *p<0.1; **p<0.05; ***p<0.01. This table reports estimates of a probit model with *atd_conc_freeride* as the binary response and the ERFL clusters as a covariate (ERFL-HIGH as reference) along with other socio-economic attributes.

Table 13: Average marginal effects (AME) of the logit model for concern for free-riding behavior.

	AME
MID-literacy	0.002
	(0.007)
LOW-literacy	0.042^{***}
	(0.010)
female	-0.033^{*}
	(0.015)
age above 60	0.067^{**}
	(0.021)
is_sfh	-0.018^{*}
	(0.007)
languageFR	0.049^{*}
	(0.021)
languageIT	0.078^{***}
	(0.009)
age above 60:hhincome 6k-12k	-0.041^{**}
	(0.013)

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Many non-significant effects are not included here for brevity. For the literacy cluster, HIGH-literacy is the reference group. The model consisted of interaction terms with gender and age, age and income, and gender and university education.

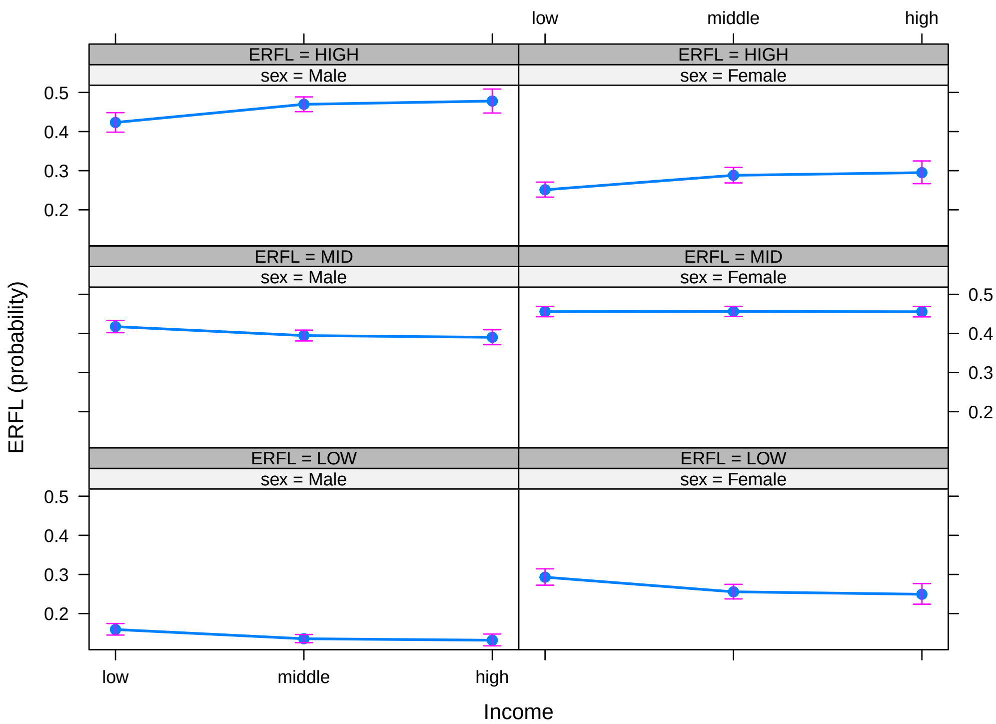

Figure 8: Effect plot of income and gender.

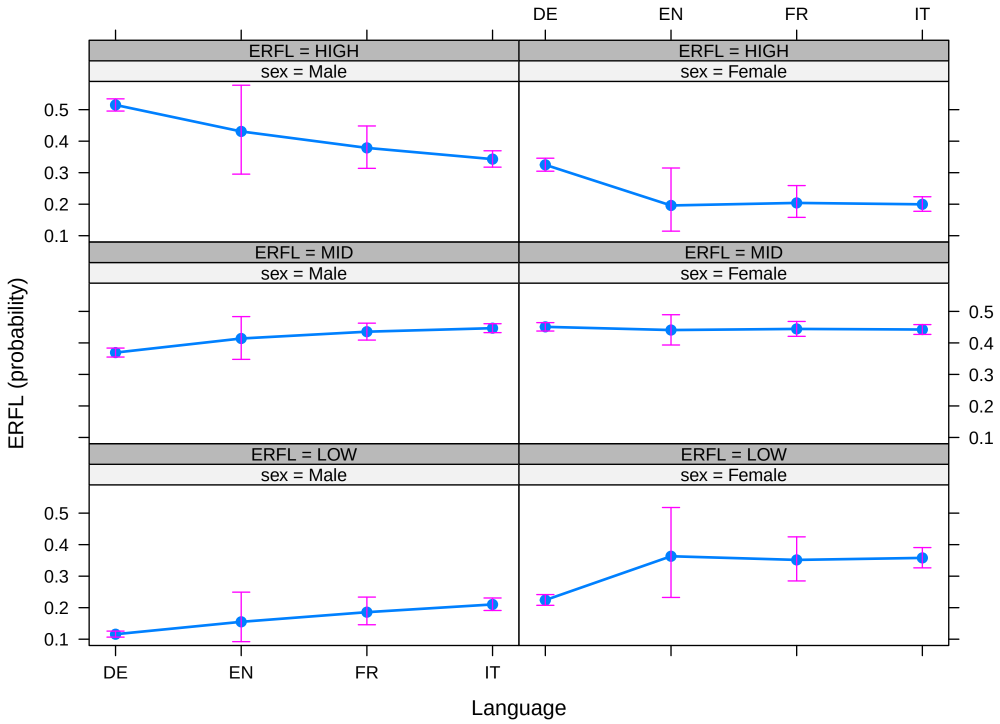

Figure 9: Effect plot of language and gender.

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