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Explaining electricity demand and the role of energy and investment literacy on end-use efficiency of Swiss households

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ABSTRACT

This paper estimates the level of transient and persistent efficiency in the use of electricity in Swiss households using the newly developed generalized true random effects model (GTREM). An unbalanced panel dataset of 1994 Swiss households from 2010 to 2014 collected via a household survey is used to estimate an electricity demand frontier function. We further investigate whether energy and investment literacy have an influence on the household electricity consumption. The results show significant inefficiencies in the use of electricity among Swiss households, both transient (11%) and persistent (22%). We note that the high persistent inefficiency is indicative of structural problems faced by households and systematic behavioral shortcomings in residential electricity consumption. These results indicate a considerable potential for electricity savings and thus reaching the reduction targets defined by the Swiss federal council as part of the *Energy Strategy 2050*, wherein end-use efficiency improvement is one of the main pillars. The results support a positive role of energy and, in particular, investment literacy in reducing household electricity consumption. Policies targeting an improvement of these attributes could help to enhance efficiency in the use of energy within households.

1. Introduction

In Switzerland, electricity is primarily produced by hydropower plants (60%) and nuclear power plants (40%). In 2011, after the Fukushima Daiichi nuclear accident, the Swiss federal council decided to abandon nuclear energy. For this reason, the Swiss federal council developed a new energy policy concept, called *Energy Strategy 2050*. One important goal of this strategy is to reduce electricity consumption by improving the level of efficiency in the use of electricity and to increase the share of electricity produced with new renewable sources of energy such as wind and solar. The efficiency improvement and the development of new renewable sources should, therefore, allow substituting the amount of electricity produced by nuclear power plants. In this context, the residential sector is characterized by great potential for energy efficiency gains and could make an important contribution to a reduction of total end-use electricity consumption.[1]

Against this background, it is important for policy makers to have information on the potential for electricity savings in the residential sector. Moreover, it is important to know which are the determinants that influence the level of efficiency in the use of electricity. A low level of efficiency, as discussed in Filippini and Hunt (2015), may be due to the fact that households do not adopt and use energy efficient appliances or do not use their appliances in an optimal way. For instance, a household might postpone substituting an old and inefficient refrigerator that consumes a lot of electricity, or does not use a cooling system or washing machine in the most efficient way.

The determinants of residential energy efficiency have been widely covered in the economic literature (Gillingham et al., 2009; Allcott and Greenstone, 2012; Frederiks et al., 2015). The potential explanations for an inefficient use of appliances on the one hand

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[1] Although we have sometimes used the general term ‘energy’ in the discussions, the reader is informed that the analysis in this research refers to ‘electricity’ consumption at the residential level.

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and for an under-investment in energy-efficient household appliances on the other can be attributed to either market failures or behavioral failures (Broberg and Kazukauskas, 2015). Market failures that prevent investments in energy-efficient appliances can take the form of information problems (e.g., lack of information and information asymmetries), misplaced incentives and principal-agent problems such as the landlord-tenant problem. But even if these market failures could be overcome, several behavioral failures such as bounded rationality, loss aversion, status-quo bias, risk aversion or inattentiveness[2] potentially reduce the level of efficiency in a household's energy use. All these behavioral failures tend to prevent households from identifying the appliances that minimize lifetime costs or from using the appliances in an efficient way. However, as shown by Blasch et al. (in press), households that are scoring high with respect to investment and energy literacy seem to be less prone to boundedly rational behavior.

To our knowledge, relatively few studies have looked into the relationship between energy and investment literacy and residential energy efficiency (for an example, see Brounen et al. (2013)). Investment literacy can be defined as the ability to perform an investment analysis and to calculate the lifetime cost of an appliance or energy-efficient renovation. Energy literacy can be defined as an individual's cognitive, affective and behavioral abilities with respect to energy-related choices. According to DeWaters and Powers (2011), energy literacy comprises an individual's or household's *(1)* knowledge about energy production and consumption and its impact on the environment and society; *(2)* attitudes and values towards energy conservation; and *(3)* corresponding behavior. In this paper, we therefore put particular emphasis on examining the influence of energy literacy, investment literacy and energy-saving behavior on a household's level of efficiency in the use of electricity.[3]

Hence, in this paper, we provide an answer to the following questions: Which are the factors that influence the electricity demand at the household level? What is the level of efficiency in the use of electricity of Swiss households? How large are the potentials for energy savings in the residential sector for a given level of energy services? Does a household's level of energy and investment literacy influence its level of efficiency in the use of electricity?

To answer these questions, it is important to remember that a household's energy demand is not a direct demand for energy or electricity, but rather a derived demand for the production of energy services such as warm food, clean clothes and lit rooms. Therefore, behind electricity demand there is a production function. A reduction in energy consumption for the production of a given level of energy services can be achieved either by improving the level of efficiency in the use of inputs (i.e. in the use of appliances), or by adopting a new energy-saving technology (i.e. purchase of new appliances, investments in energy-saving renovations), or both. Technological change can induce a reduction of energy consumption for a given level of energy services, provided that the inputs are used in an efficient way, i.e. given that the households are productively efficient. The total reduction in residential energy consumption is therefore a result of the interplay of technological change and a household's behavior.[4]

The level of energy efficiency of households can be measured with a bottom-up approach, by making an on-site efficiency analysis of buildings. However, with such an economic-engineering approach, the behavioral aspects in energy use are often not accounted for. In addition, this approach is not based on the microeconomics of production. In this paper, we therefore estimate a household's level of energy efficiency with econometric methods, accounting for total electricity consumption and factors such as the size and characteristics of the dwelling, household composition and other socioeconomic attributes, level of energy services consumed, energy literacy, investment literacy and energy-saving behavior. With this approach a broader and more adequate bench-marking of Swiss households with respect to their electricity consumption can be performed.

The existing literature on the measurement of the level of energy efficiency in the residential sector using an economic approach is relatively sparse. While the Stochastic Frontier Analysis (SFA) has been used with aggregated energy data (e.g., Filippini and Hunt, 2012; Filippini et al., 2014), we use dis-aggregated data since residential consumers are typically very heterogeneous and household level data can add more detail to the knowledge of consumer response. Weyman-Jones et al. (2015) are one of the first to estimate energy efficiency using SFA with dis-aggregated household survey data. They estimate an energy input demand frontier function, originally proposed by Filippini and Hunt (2011), using a cross-sectional household dataset from a survey in Portugal. However, the model used by Weyman-Jones et al. (2015) is relatively simple with only a few explanatory variables. In contrast, Boogen (2017) uses a much richer model using not only the information on appliance stock but also on the amount of energy services consumed to estimate the technical efficiency of a set of Swiss households using a sub-vector distance function. However, as Boogen (2017) uses a cross-sectional dataset, the unobserved heterogeneity cannot be accounted for. Moreover, only the level of technical efficiency is estimated. Alberini and Filippini (2015) employ an energy demand frontier approach similar to Weyman-Jones et al. (2015) using a large panel dataset from US households to estimate the level of energy efficiency. By using panel data they are able to distinguish and estimate the level of persistent and transient energy efficiency.[5] The limitation of Alberini and Filippini (2015) is that the amount of energy services consumed by a household was not included as an explanatory variable.

In this paper, we follow the energy demand frontier approach using an unbalanced panel dataset of 1994 Swiss households from 2010 to 2014. Moreover, using an approach proposed by Coelli et al. (1999), we will also measure the level of efficiency by comparing the electricity consumption of all households to the optimal level obtained from an energy input demand frontier function associated with a high level of investment literacy.

The contribution of this paper is twofold – firstly, we estimate the persistent and transient efficiency in electricity consumption of a large sample of Swiss households and demonstrate an application of the newly developed GTREM model (Colombi et al., 2014; Filippini and Greene, 2016) that estimates both types of efficiency conveniently by a simulated maximum likelihood approach. We benefit from a unique panel dataset covering a five-year period collected via a household survey conducted in 2015. The dataset includes information on the level of energy services, which is usually not measured as it can be difficult to collect this information.[6] Information on the level

[2] Note that inattention to potential electricity savings may be justified on rational grounds (Sallee, 2014), especially if electricity prices are very low in relation to household income such that electricity costs are a marginal position in the household's budget. In such a case the consumer may anticipate that the information and search costs related to the purchase of a new appliance may outweigh the potential future energy savings.

[3] We consider a slightly narrower definition of energy literacy (described in Section 2) in this study.

[4] For a discussion on the concept of energy efficiency based on the production theory and on the measurement methods, see Filippini and Hunt (2015).

[5] The concept of persistent and transient efficiency was introduced by Colombi et al. (2014) and significantly developed by Filippini and Greene (2016).

[6] Generally, the energy services are approximated by household characteristics that influence the level of energy services in a household, e.g., in Alberini and Filippini (2015).

of energy services is a critical issue when using SFA (Filippini et al., 2014). Finally, to our knowledge, this paper is the first to provide a systematic analysis of the impact of both energy and investment literacy on the total electricity consumption of households while controlling for the effects of the general level of education of the household members. Our results can therefore provide new insights into the interrelations between the literacy and education variables and their role for transient and persistent efficiency in residential electricity consumption.

The rest of the paper is organized as follows. Section 2 discusses the role of energy literacy and investment literacy for energy efficiency. Section 3 presents an econometric model of residential electricity demand using dis-aggregated household data and discusses the empirical specifications for estimating the level of efficiency in the use of electricity. Section 4 describes the household survey data and the variables used in the model. Section 5 presents the results and Section 6 concludes.

2. Energy and investment literacy

Residential energy efficiency is a function of the efficiency of the inputs used to produce a certain energy service (type of appliance) and of the efficiency in the use of these inputs (use of appliance). Both the choice of electric appliances and the efficiency of their use are necessarily influenced by the user's knowledge about the baseline energy consumption of an appliance and how it can be steered by a specific user behavior, such as switching it off after use rather than leaving it on stand-by. The choice of appliances requires, in addition, some ability to evaluate different appliances with respect to their lifetime cost, accounting for the initial purchase price and the future spending on its electricity use. This evaluation requires complex calculations that are based on assumptions about the expected lifetime of the appliance, the electricity price now and in the future, as well as on the anticipated intensity of use of the appliance. The decision-maker thus does not only need to dispose of knowledge about the electricity price and the consumption of the appliance but also of the ability to calculate and to compare the net present values of several appliances to choose from (Sanstad and Howarth, 1994a; Sanstad and Howarth, 1994b; Scott, 1997; Gerarden et al., 2015).

Making these calculations can be burdensome for consumers, as suggested by the results presented in Allcott and Taubinsky (2015). Participants of an online randomized control trial in the US could choose between light bulbs with different levels of energy efficiency. If information about total lifetime cost of the light bulbs was provided, more consumers opted for the more efficient compact fluorescent light bulbs compared to the control condition. Also Blasch et al. (in press) test whether providing consumers with information about the average yearly electricity cost for an appliance increases the probability that they opt for a more efficient appliance. They find a significantly positive relationship between the provision of monetary information on electricity consumption and the probability to perform an investment calculation rather than following a decision-making heuristic, and hence the probability to choose a more efficient appliance. In addition, they also find a positive impact of an individual's level of energy and investment literacy on the choice of the more efficient appliance.

A definition of what energy literacy comprises can be found in DeWaters and Powers (2011). According to them, energy literacy entails a cognitive (knowledge), affective (attitudes, values) and behavioral component. In our study, we focus on the cognitive aspect of energy literacy and add the dimension of investment literacy measured by a compound interest rate task. Compound interest rate tasks are frequently used to elicit an individual's level of financial literacy, such as in Lusardi and Mitchell (2009) or Brown and Graf (2013). Lusardi and Mitchell (2009) provide evidence that individuals who know about interest compounding are 15 percentage points more likely to be retirement planners (Lusardi and Mitchell, 2007). Brown and Graf (2013) find in a study on financial literacy in Switzerland that respondents scoring high on financial literacy are more likely to have an investment related custody account and to make voluntary retirement savings. That investment literacy may also be related to the choice of efficient appliances is suggested by results provided in Attari et al. (2010) who show that US citizens with a higher affinity to numerical concepts had more accurate perceptions of the energy consumption of different household appliances than their peers. Additionally, Brent and Ward (2017) show in a recent paper using a discrete choice experiment for the purchase of hot water systems that a higher financial literacy score also increases the willingness to pay for reduced operating cost.

Whether, and if yes, how strongly, an individual's energy-related knowledge and ability to make complex calculations eventually impacts on the final energy consumption of the individual's household is an interesting question to ask. If there is a significant influence, educating individuals about energy-related issues and instructing them how to perform an investment calculation would be a potential lever to enhance residential end-use energy efficiency. Nationwide education campaigns, for example also in schools, could give a strong boost to energy efficiency of households.

So far, only a few studies have investigated the relationship between energy and investment literacy and actual energy consumption of households. As one of them, Brounen et al. (2013) study the influence of energy and investment literacy on conservation behavior of households in the Netherlands. Analysing data from a large national household survey, they find that energy literacy among households is very low. For example, only about half of the respondents are aware of the monthly amount they spend on energy consumption and about 40% were not able to correctly evaluate an investment into new and more energy-efficient equipment. Yet, they do not observe a significant effect of energy literacy on a household's self-reported energy consumption, and also not on a household's choice of the thermostat setting.

Mills and Schleich (2012) analyze how strongly the level of general education influences a household's energy use behavior and adoption of more efficient appliances based on survey data collected in 11 European countries. They observe a significantly positive influence of the level of education of the household head on the adoption of more efficient appliances (measured by an energy-efficient technology adoption index). In addition, they build an energy-use-knowledge index and find that the level of the index rises if the household head holds a university degree and is lowest if the household head holds a vocational degree. University education of the household head also impacts positively on the energy conservation index the authors built. Apart from these studies, Zografakis et al. (2008) report results from a small-scale energy-related information and education project in Greece that impacts positively on stated energy-saving behaviors of students and their parents. Overall, there is thus no conclusive evidence on the role of energy and investment literacy for the total energy consumption of a household, especially if the effect of the general level of education of the household members is accounted for.

3. An econometric model for electricity demand

Within the framework of household production theory, energy demand is derived from the demand for energy services. We assume that households purchase inputs such as energy and capital (household appliances) and combine them to produce outputs which are the desired energy services such as cooked food, washed clothes or hot water – which appear as arguments in the household's utility function (Muth, 1966; Flaig, 1990. Within this theoretical framework, it is possible to derive the optimal input demand functions for energy and capital (Flaig, 1990; Alberini and Filippini, 2011). Conventional theory assumes perfect knowledge of technical relationships and prices, and results in a situation characterized by overall productive efficiency[7] in the production of energy services. In practice, however, inefficiencies in the use of the inputs, i.e. combinations of inputs that do not minimize costs, are likely to occur.

Filippini and Hunt (2011, 2015) propose a non-radial input specific measure of efficiency in the use of energy based on the difference between the optimal use of energy (one which minimizes input costs) and the observed use of energy. In this paper, we follow this approach and estimate a measure of efficiency in the use of electricity based on the estimation of a single conditional input demand frontier function, i.e. the demand function for electricity. The function represents the minimum or baseline electricity demand of a model household that has a highly efficient appliance stock and uses the most efficient production process to produce a given level of energy services, given electricity price, price of capital stock and other factors. If a household is not on the frontier, the distance from the frontier measures the level of inefficiency in the use of electricity. In our empirical work, which uses dis-aggregated data from Swiss households, we posit the following household electricity demand function:

$$\begin{aligned}\ln E_{it} = \alpha_0 + \alpha_p \ln p^E_{it} + \alpha_M M_{it} + \alpha_H H_{it} + \alpha_{ES} ES_{it} + \alpha_L LOC_{it} \\ + \alpha_w W_{it} + \alpha_{LT} LIT_{it} + \alpha_{BE} BEH_{it} + \alpha_T T_t + \alpha_{TT} T^2_t + \varepsilon_{it} \qquad (1)\end{aligned}$$

where E_{it} is the electricity demand (in kWh), p^E_{it} is the electricity price, M_{it} is a vector of household characteristics, H_{it} is a vector of dwelling characteristics, ES_{it} is the amount of energy services consumed, LOC_{it} is the utility service area and W_{it} is the number of heating degree days (HDD) and cooling degree days (CDD) that the household experiences. LIT_{it} represents the level of energy and investment literacy of the respondent, BEH_{it} captures the energy saving behavior of the household, T_t and T^2_t capture the time trend, and ε_{it} is the overall error term. This equation represents the minimum electricity consumption as a function of electricity price, weather influences, household and dwelling characteristics, stock of special appliances[8], level of energy services, energy and investment literacy, and energy saving behavior. We use a log-log model specification in the empirical analysis presented in this paper.

Note that it would be possible to include many non-linearities (beyond those implied by the log-log setting) and higher order dependencies in the model specified in Eq. (1). A quadratic time trend is an example. It is also plausible that an additional household member does not necessarily increase the energy demand linearly. Other variables like weather or electricity prices may as well have different effects in different regions. However, if too many non-linear terms are included, convergence problems within the estimation procedure may arise. In our log-log model specification we decided to include a quadratic time trend.[9]

In order to obtain the level of efficiency in the use of energy, we estimate Eq. (1) using the stochastic frontier function approach introduced by Aigner et al. (1977). Traditionally, the SFA approach has been used in production theory to empirically assess the economic performance of production processes. The basic idea is that the frontier function estimates the maximum (or minimum) level of an economic indicator reachable by a decision making unit, e.g., a firm or an economic agent like a household. In the case of residential electricity consumption, the frontier gives the minimum level of electricity input used by a household for any given level of energy services. The difference between the observed input and the optimal input demand on the frontier represents inefficiency. Furthermore, the difference between the observed input and the cost-minimizing input demand on the frontier depicts both technical as well as allocative inefficiency (Kumbhakar and Lovell, 2000).

In the SFA approach the so called error term ε_{it} is composed of several components. One of these is a symmetric disturbance capturing the effect of noise assumed to be normally distributed as usual. The other components, discussed in details in Section 3.1, are interpreted as an indicator of the inefficient use of electricity at the household level.

3.1. Estimation methodology

There are several econometric models available for estimating a stochastic frontier using panel data. Below we briefly mention some of the most commonly used models in empirical analysis.

The first is the basic random effects model by Pitt and Lee (1981) (REM hereafter). Next is the true random effects model (TREM hereafter) proposed by Greene (2005a,b) and the third is the generalized true random effects model (GTREM hereafter) by Colombi et al. (2014) and Filippini and Greene (2016).[10] As discussed in Filippini and Greene (2016), some of these models estimate time invariant values of the level of efficiency (persistent efficiency) whereas others produce time variant values (transient efficiency).

The REM by Pitt and Lee (1981) overestimates the level of inefficiency since it regards any time-invariant and group-specific unobserved heterogeneity as inefficiency. The REM does not provide an estimation of the time-varying transient inefficiency indicator. On the other hand, the TREM by Greene (2005a,b) controls for time-invariant unobserved heterogeneity, but any time-invariant component of inefficiency is then completely absorbed in the household-specific constant terms. Hence this model tends to underestimate the level of inefficiency and as such gives only a measure of the transient inefficiency and not of any time-invariant persistent inefficiency.

In the context of a household, the persistent inefficiency component might relate to the presence of structural problems in the production process of energy services like an old electrical appliance stock or old buildings with very poor insulation. It might also relate to systematic behavioral shortcomings like frequently opening the windows in the heating period and not switching off the lights after use. Similarly, the transient inefficiency part might point towards the presence of non-systematic behavioral failures that could be solved in the short term, e.g., the use of an additional cooling appliance for a few weeks during a hot summer, or the temporary presence of guests visiting the household, hence increasing the demand for energy services temporarily.[11]

This paper focuses on the third and the most recent model, the GTREM, which offers the possibility to simultaneously estimate the

[7] As defined by Farrell (1957).

[8] Eq. (1) should be interpreted as a long-run electricity demand function, because the capital stock can vary. We just include a few variables to take into account the presence of a second fridge, a separate freezer, and whether or not the household owns a special appliance, such as a sauna. Further, the price for appliances is assumed to be the same for all households.

[9] We tried other higher order terms and found that the obtained value of the two types of efficiencies are extremely similar (correlations in the range 0.994 – 0.999) when compared to the results from the specification presented here. Furthermore, the coefficients on our parameters of interest (i.e. the two literacy variables) were also comparable.

[10] See Tsionas and Kumbhakar (2014) and Filippini and Greene (2016) for an overview of all these models. The reader is also referred to Filippini and Hunt (2015) who provide a summary of different econometric specification and comparison between these models.

[11] Although such a distinction between transient and persistent inefficiency has been partially neglected in empirical studies, we believe it will gain much more importance in future research. This distinction is crucial with respect to the choice of policy instruments to improve end-use energy efficiency.

Table 1
The GTREM specification for the stochastic cost frontier.

Model: $y_{it} = \alpha + \boldsymbol{\beta}'\mathbf{x}_{it} + \varepsilon_{it}$	
Full random error (ε_{it}):	$\begin{cases} \varepsilon_{it} = w_i + h_i + u_{it} + \nu_{it} \\ u_{it} \sim N^+\left[0, \sigma_u^2\right] \\ h_i \sim N^+\left[0, \sigma_h^2\right] \\ \nu_{it} \sim N\left[0, \sigma_\nu^2\right] \\ w_i \sim N\left[0, \sigma_w^2\right] \end{cases}$

Note: A log-log model specification is used in the empirical analysis.
E($h_i|\mathbf{y}_i$) captures the persistent inefficiency and E($u_{it}|\mathbf{y}_i$) captures the transient inefficiency.

persistent and transient parts of inefficiency. Colombi et al. (2014) provided a theoretical construct that distinguishes between persistent and transient inefficiency and Filippini and Greene (2016) have developed a straightforward empirical estimation method for the GTREM by exploiting the Butler and Moffitt (1982) formulation in the simulation. The GTREM is obtained by adding to the TREM a time persistent inefficiency component in the time varying stochastic frontier.

As shown in Table 1, this model has a four-part disturbance term with two time-variant and two time-invariant components. One of these components (h_i) captures the persistent inefficiency in the use of energy that may be due to regulations, investments in inefficient appliances or buildings, or habits and consumption behaviors that tend to waste energy. Another component (u_{it}) captures the transient inefficiency that may be, e.g., due to non-optimal use of electrical appliances or heating systems. In the short run, even in the presence of some inflexibility, a household may be able to adjust the use of appliances and heating systems. The remaining two components are assumed to be normally distributed and they respectively represent a symmetric disturbance capturing the effect of noise (ν_{it}) and time-invariant household specific effects (w_i).

To understand how the four different components of the error term could be separately identified, we emphasize the crucial insight noted in Filippini and Greene (2016) that the four part disturbance should be instead visualized as only a two part disturbance. One of the parts is time varying ($u_{it} + \nu_{it}$) and the other is time invariant ($w_i + h_i$), and both parts follow their own skewed normal distribution (rather than normal distribution). Within the simulated likelihood approach, it then follows that the TREM could be easily extended for the purpose of identifying the inefficiencies in a GTREM model. It is a trivial step to simulate draws from a skewed normal distribution as the sum of a normal plus the absolute value of a normal draw (see Filippini and Greene (2016, p. 191–192) for a complete discussion).

The approach used here therefore relies on the approximation of the level of the energy efficiency of Swiss households by two one-sided non-negative terms, u_{it} and h_i.[12] Following Filippini and Greene (2016), the level of efficiency in the use of electricity can be expressed in the following way:

$$EF_{it} = \frac{E_{it}^F}{E_{it}} \tag{2}$$

where E_{it} is the observed electricity consumption and E_{it}^F is the frontier or minimum demand of household i in year t. An electricity efficiency level of one indicates a household on the frontier, thereby implying an efficiency level of 100%. Households that are not located on the frontier receive efficiency scores below one, thereby implying the presence of inefficiency in household electricity consumption.

4. Data

The data for this research was gathered by means of a large household survey in cooperation with six Swiss utilities.[13] Utilities operating in urban and suburban areas were selected in order to get a sample of households as homogeneous as possible in terms of environment. The participating utilities invited either all or a sub-sample of their customers to take part in an online survey. If sub-samples of customers were drawn, all household customers had the same probability of being in the sample. The invitation letter was sent either separately or accompanying a bi-monthly, quarterly or yearly electricity or gas bill.[14]

The survey questionnaire was developed based on insights from the survey methodology literature (Dillman et al., 2009; Groves, 2004), reviewed by several experts in the field of residential energy-efficiency and pre-tested on a student sample. It included questions on dwelling characteristics, socioeconomic attributes, appliance stock and the level of energy services consumed by the household. In addition, the survey comprised questions about the respondents' environmental attitudes, energy saving behavior at home, energy-related literacy and investment literacy.

At the end of the survey questionnaire, sociodemographic characteristics such as age, gender, employment status and level of education of the respondent were recorded. On completion, respondents were asked whether they agreed that the survey data be linked to the actual energy consumption data of their household. In case of the consumer's accordance, the actual electricity consumption data from 2010 to 2014 was linked to the survey data of the respective household to allow a joint analysis.

After accounting for the correct target group[15], incomplete responses, and duplicate entries, we have valid and complete data for 1375 (Lucerne), 583 (Bellinzona), 877 (Biel), 1406 (Lugano), 739 (Winterthur) and 826 (Aarau) survey respondents.[16] The observed samples are supposed to reflect the Swiss population living in urban (and sub-urban) areas, which accounts for about three quarters of the total population.[17] Of all respondents who started the online survey, filled in their customer number and were filtered-in as the target group, almost 88% completed the survey. We do not find any significant selection among the sample of usable surveys relative to the target group.

[12] The estimation procedures are readily available in NLOGIT (Greene, 2012). In this paper, the models were estimated using NLOGIT 5.

[13] The six utilities are Aziende Industriali di Lugano (AIL), IBAarau (IBA), Stadtwerk Winterthur (SW), Energie Service Biel/Bienne (ESB), Energie Wasser Luzern (EWL), Aziende Municipalizzate Bellinzona (AMB) that operate respectively in (and the surrounding areas of) Lugano, Aarau, Winterthur, Biel/Bienne, Lucerne and Bellinzona. Among these regions, Aarau, Winterthur and Lucerne are German speaking; Lugano and Bellinzona are Italian speaking; and Biel/Bienne is bilingual (German/French speaking).

[14] The response rates (defined as share of survey page visits over total number of invited customers) varied between 3.2% and 7.4%.

[15] The target group consists of respondents (i) for whom the electricity/gas bill refers to their primary residence; (ii) who moved in their current residence before 01.01.2015; and (iii) who are one of the persons in their residence who decides about the purchase of goods and/or pays the bills. All three samples combined, a total of 6688 respondents were filtered-in as the target group, of which 5917 completed the survey.

[16] The usable survey response rates for all the six survey regions are relatively low when compared to the number of invitation letters sent. One reason for this is the setting – the invitation to participate was sent on paper, including a link to the online survey. This invitation was sent with one of the regular utility bills, which unfortunately lowered the probability that it got the customers' attention.

[17] Data from the Swiss cities association (SSV) 2017.

To evaluate how well our subsamples reflect the basic demographic characteristics of the six urban areas included in our analysis, we compare the sample characteristics to population statistics from the Swiss cities association (see Table 7 in the Appendix). In terms of gender composition, the households in our samples seem to represent the population in the six areas quite well. The same holds for age-groups, with some exceptions such as the samples from Bellinzona, Lugano and Aarau, in which a slight deviation can be observed (higher share of younger as compared to older household members in Bellinzona and Lugano, higher share of both younger and older household members as compared to the group of people aged 20 to 64 years in Aarau). Regarding the mean household size, we observe that households in our sample comprise slightly more people than the average household in the areas. Also the living space per person (m^2/person) is slightly above average in all six regions. This, however, does not hold for the number of people per room, which is mostly at the average level. The only exception is Biel/Bienne, where fewer people per room are observed than the population mean would suggest. In conclusion, the characteristics of the surveyed households are generally in line with the characteristics in the six areas (with some smaller exceptions). It is to be noted that the statistics at the city level may not completely reflect the statistics of the surveyed areas, i.e. the service areas of the utilities, which usually also include neighboring municipalities.

The variables used for the household electricity demand estimation are explained below and an overview of the summary statistics can be found in Tables 2 and 3.

Table 2
Summary statistics (unbalanced panel of 1994 households).

Variable	Mean	Std. dev.	Min.	Max.	N
Panel variables…					
Q_E	3122.77	2326.19	501	38124	8295
MP_AVG	18.68	2.47	13.06	24.32	8295
HHSIZE	2.36	1.19	1	6	8295
INC6K	0.3	0.46	0	1	8295
INC6_12K	0.52	0.5	0	1	8295
INC12K	0.18	0.39	0	1	8295
HDD	2949.75	386.83	1925.6	3602.2	8295
CDD	177.31	86.79	73	458.6	8295
IS_SFH	0.29	0.46	0	1	8295
SQM	122.69	54.41	20	400	8295
BLT1940	0.19	0.39	0	1	8295
BLT1970	0.26	0.44	0	1	8295
BLT2000	0.37	0.48	0	1	8295
BLT2015	0.17	0.38	0	1	8295
MINERGIE	0.07	0.26	0	1	8295
WABS5TO8	0.08	0.27	0	1	8295
HAS_FR2	0.19	0.39	0	1	8295
HAS_FREEZER	0.53	0.5	0	1	8295
NONE_APPL	0.68	0.46	0	1	8295
COOKEL	0.89	0.31	0	1	8295
LUG	0.26	0.44	0	1	8295
AAR	0.11	0.31	0	1	8295
WINT	0.13	0.34	0	1	8295
BIEL	0.18	0.39	0	1	8295
LUZ	0.24	0.42	0	1	8295
BELL	0.08	0.27	0	1	8295
UNIV	0.36	0.48	0	1	8295
UNIV_PAR	0.17	0.38	0	1	8295
Cross-sectional variables (2014)…					
HAS_YOUN	0.23	0.42	0	1	1994
HAS_ELDE	0.31	0.46	0	1	1994
NMEALS	8.52	3.41	0	14	1994
NDISHWCY	2.99	2.32	0	8	1994
NWASHING	3.04	3.82	0	30	1994
NENTT	6.57	4.99	0	44	1994

4.1. Dwelling characteristics

The residence-related attributes comprise non-varying features of the dwelling like the area size in square meters (`SQM`), the time-period when the building was built[18], a dummy indicating whether the dwelling is built according to the Minergie standard, a standard for efficient buildings in Switzerland, (`MINERGIE`)[19] and another binary variable captures whether the household uses electricity for cooking (`COOKEL`). It is also known in which of the six utility service areas the dwelling is located.

4.2. Household composition and socioeconomic attributes

With respect to household composition, our data set includes information on the presence of children/teens younger than 20 years (`HAS_YOUN`), or elderly person above 64 years (`HAS_ELDE`) in the household at the end of the year 2014. The total number of people who have regularly lived in the residence between 2010 and 2014 (i.e. yearly household size `HHSIZE`) is accounted for. Furthermore, the households reported the average number of weeks per year during which their residence remains unoccupied, e.g., due to longer work-related assignments, vacations or stays at a second home (`WABS5TO8` is 1 if the residence remains unoccupied 5–8 weeks per year). Finally, with respect to the level of education, we also capture whether the survey respondents (`UNIV`), as well as their partners (`UNIV_PAR`), hold a university degree.[20]

Monthly gross household income is captured by dummies representing three income classes: less than CHF 6000 (`INC6K` as reference); between CHF 6000 to 12,000 (`INC6_12K`); and more than CHF 12,000 (`INC12K`).

4.3. Energy services

Information on the consumption level of several energy services is available – number of warm meals prepared per week (`NMEALS`), which is the sum of total number of prepared lunches and dinners in a typical week; number of dishwasher cycles in a typical week (`NDISHWCY`); number of washing-related cycles per week (`NWASHING`), which is the sum of total number of washing machine and clothes dryer cycles in a typical week; number of entertainment services consumed per day (`NENTT`), which is the sum of total hours of typical daily usage of all the TVs (CRTs and flat-screens) and computers (desktops and laptops) within the residence.

Two dichotomous variables indicate whether the household owns a second fridge (`HAS_FR2`) or a separate freezer (`HAS_FREEZER`). Another binary variable captures whether the household owns

Table 3
Overview of energy literacy, investment literacy and energy saving behavior.

Variable	Mean	Std. dev.	Min.	Max.	N
ENLIT	4.39	2.84	0	11	1994
INVLIT	0.71	0.45	0	1	1994
BEHAV	2.35	1.05	0	4	1994

[18] In four categories: before 1940 (`BLT1940`) as reference; 1940–1970 (`BLT1970`); 1970–2000 (`BLT2000`); and after 2000 (`BLT2015`).
[19] The Minergie certificate can be acquired not only for new buildings but also for renovated buildings.
[20] `UNIV` and `UNIV_PAR` is 1 if a person holds a degree from a university, university of applied sciences or university of teacher education.

a special energy intensive appliance or equipment like an air-conditioner.[21] These three variables are used as simple proxies for the corresponding energy services.

4.4. Weather

The yearly weather related information comprises the total number of heating degree days (HDD) and cooling degree days (CDD) which is measured at a weather station that is located in, or nearby, each of the six different service regions.[22] As the service regions of the utilities in our dataset are mostly city utilities, the service areas are geographically relatively small, therefore, all households in one service area are matched to the same weather station.

4.5. Electricity consumption

The yearly electricity consumption (response variable Q_E) ranges from 501 kWh to 38, 124 kWh, with a mean value of about 3123 kWh.[23] The residential sector can be highly heterogeneous in terms of electricity consumption. For example, dwellings with an electricity based space or water heating system would be expected to consume much larger amounts of electricity compared to the dwellings using oil or gas based heating. Since we are interested in measuring the *inefficiency in the use in electricity*, households having an electricity-based space or water heating system (including heat pumps) were excluded from the sample as these would exhibit significantly higher electricity consumption than households with non-electricity-based heating systems.

Within the context of estimating a demand function, concerns relating to the price of electricity being endogenous (in short and/or long run) is typical. To overcome this, we use marginal prices that do not directly depend upon the individual electricity consumptions but are defined using the default electricity tariff for each utility over the 5 years. The electricity price during the period 2010–2014 is measured as an average of the peak and off-peak marginal prices using a representative average time-of-use share of peak consumption as weight.[24] Endogenous prices would have been a serious issue if we were using electricity prices based on individual electricity consumption. Moreover, it is worth pointing out that we are not interested in estimating the price elasticity in this study.

From the sample, we also exclude the households who reported that, on average, their residence in completely unoccupied either for more than 8 weeks a year, or for more than 4 days a week (e.g., due to regular travel for work). Lastly, we have an unbalanced panel data comprising of households for which electricity consumption in the same residence for at least 2 out of the 5 time periods from 2010 to 2014 is available.[25] Due to this, all the 1994 households are not represented in every period, but at least in any two or more of the five periods. The descriptive statistics of most of the main variables appear to be similar across all periods (Table 8 in the Appendix).

4.6. Energy and investment literacy

Energy literacy was measured by an index that accounts for several dimensions of energy literacy: knowledge of the average price of 1 kWh of electricity in Switzerland, knowledge of the usage cost of different household appliances (running a PC for one hour, running a washing machine cycle with full load) as well as knowledge of the electricity consumption of various household appliances. For example, respondents were given two energy services and were asked which of the two consumed more electricity or whether they consumed about the same, e.g., boiling 1 liter of water on a stove compared to boiling 1 liter of water using an electric kettle. Responses to all these questions were combined into a simple measure of energy literacy by assigning a certain amount of points for each correct answer. Depending on the number of correctly answered questions, respondents could achieve a value between 0 and 11 on the energy literacy score (ENLIT).

Investment literacy (INVLIT) was measured by a binary variable that takes the value one if the respondent correctly solved a compound interest rate calculation. Compound interest rate calculations are usually used to assess an individual's investment literacy (Lusardi and Mitchell, 2007; Lusardi and Mitchell, 2009; Brown and Graf, 2013).

Similar to findings reported in the study of Brounen et al. (2013), we observe a rather low level of energy literacy in our sample. For example, only about 27% of the respondents knew about the average price of electricity in Switzerland. Regarding the level of investment literacy among Swiss consumers, we find that 71% of the participants in our survey were able to correctly solve the compound interest calculation.

4.7. Energy-saving behavior

One section of the survey asked respondents whether they exercised certain energy-saving behaviors when consuming energy services at home. The respondents had to indicate their agreement on a 5-point likert scale ranging from 'strongly disagree' to 'strongly agree' with respect to these behaviors – completely switching off electronic appliances after use (no standby); running the washing machine only on full load; washing clothes on a lower water temperature of less than 30° C; and selecting a dishwasher program cycle based on the level of dirtiness. From these four types of energy-saving behavior we calculated an index score. The household received one index point for each of these behaviors if they stated that they exercised this behavior 'always' or 'very often'. Therefore, the values of the score lie within the range from 0 to 4 points (BEHAV).

An overview of the energy-saving behavior score, the energy literacy score and investment literacy can be found in Table 3. The survey questions are presented in Figs. 1–5 in the Appendix.

Next we estimate the ad-hoc electricity demand in Eq. (1) wherein we use a log-log specification. The transformation to logs

[21] The variable NONE_APPL takes the value 1 if a household reports that it does not own any of these appliances: home theater system, electric/hybrid car, swimming pool, jacuzzi, sauna, solarium, water-bed, aquarium/terrarium, air conditioner(AC) or infra-red heater.

[22] HDD and CDD data is gathered from *MeteoSchweiz* and is based on SIA (1982) and ASHRAE (2001) respectively.

[23] Given the context of household electricity consumption, we impose a minimum yearly consumption of 500 kWh.

[24] The yearly marginal electricity prices were obtained from the tariff-sheets of each of the six utilities in our sample. In order to avoid any endogeneity problems, instead of individual share of peak consumption (i.e. $[E_{peak}/E_{total}]_{it}$), we use a representative mean value of the share of peak consumption over 8 broad household categories (defined by ElCom) across the 6 regions and from 2010 to 2014 ($\overline{TOU}_{peak}$) so that there is some variation in prices over the 5 years. For customers on a time-of-use tariff system (peak = p; off-peak = op), we used $p^E_{it} = \overline{\mathrm{TOU}}_p \cdot \mathrm{MP}_p + (1 - \overline{\mathrm{TOU}}_p) \cdot \mathrm{MP}_{op}$. For single tariff consumers (without time-of-use prices), the marginal price based on the standard single tariff was directly used.

[25] The panel is unbalanced primarily because (i) the availability of electricity consumption data (response variable) is conditional on when the households moved into their current residence; (ii) consumption data for households in the utility in Lucerne is unavailable for the year 2010; and (iii) it is required that each household has at least two years of consumption data (i.e. is a panel).

further helps to interpret estimated coefficients as a measure of *relative* change in electricity demand per unit change of a continuous explanatory variable, e.g., level of an energy service or the energy literacy score.[26]

5. Empirical results

Results for two model specifications are presented in Table 4. GTREM-1 presents estimation results for the electricity input demand frontier function defined in Eq. (1), whereas GTREM-2 presents a more traditional model without any energy services. Both specifications include energy literacy, investment literacy and the energy saving behavior of the households. The traditional specification that does not include information on energy services should lead to a lower level of energy efficiency. In fact, within this model, the households that consume a relatively high amount of energy services would be classified as less efficient than the households that consume a lower amount of energy services. This is of course not an appropriate assessment, as the fact that a household consumes more energy services could be due to special preferences and needs. In this paper, we are mainly interested in estimating the level of efficiency in the use of energy among households that consume a similar amount of energy services.

Most estimated coefficients have the expected signs and are seen to be statistically significant at the 1% level. The parameter λ, which represents the relative contribution of the transient inefficiency term over the complete disturbance term, is significant in both specifications. Further, σ_h, the standard deviation of the one-sided time-invariant component h_i is also significant. This result shows the presence of persistent inefficiency. Since we use a log-log functional form for the total electricity demand and other continuous variables in the model, the estimated coefficients on such variables can be interpreted as demand elasticities, e.g., the price elasticity is found to be statistically significant and negative.

Electricity consumption increases with dwelling size and single family houses have higher electricity consumption than households living in apartments. Compared to the buildings built before 1940 (reference category), newly built houses generally consume lower electricity, with the exception of those built between the years 1970 and 2000.

Electricity consumption also increases with household size. Households, in which elderly people of 60 years or older are present, tend to consume more electricity, whereas households with children consume less. Income levels are found to be less significant when accounting for all other variables included in the model.[27]

The coefficients for the presence of a second fridge or a separate freezer are positive and significant. Electricity consumption is higher for higher levels of energy services with stronger effects for entertainment services (televisions and computers), followed by dishwashers, and washing services. The preparation of warm meals does not appear to be significant, although using electricity as the energy source for cooking is expectedly associated with a higher demand for electricity.

Using the region of Lugano as the reference, it appears that households in the region of Bellinzona (followed by Winterthur and Lucerne) consume significantly less electricity, whereas households in the region of Biel/Bienne and Aarau consume more. In terms of weather, HDD is seen to be insignificant whereas CDD is significant and positive. One would normally expect both weather variables to be significant and positive, as both these variables should contribute to increasing electricity demand. The result shown here is likely due to identification problems since regional dummies and time trends may also capture the same effects.[28] The coefficient that captures the quadratic time trend is positive and that of the linear trend is negative. The coefficient on the dummy for a university degree of the respondent is significant and negative in both models, and that of the partner is significant and negative only in GTREM-1. This indicates that electricity consumption decreases with education. It is important to control for education when analyzing the effect of energy and investment literacy in order to disentangle the effects of education and the effect we want to measure with the literacy score.

In both GTREM specifications, the estimates of the energy literacy score, investment literacy and the behavioral index are negative and significant. This means that for households exhibiting energy-saving behavior, electricity consumption is seen to be lower. Similarly, households possessing a higher level of energy-related literacy and investment literacy are also associated with lower electricity consumption, although investment literacy seems to play a more vital role.[29] As discussed later in this section in more detail, the fact that households with a high level of investment literacy consume (ceteris paribus) less electricity, implies that it is possible to identify different demand frontier functions *conditional* on the level of investment literacy.

5.1. Level of efficiency

Using the estimations above and Eq. (2), we can estimate the level of efficiency. Table 5 provides summary statistics of the estimated efficiency levels for the two GTREM specifications.[30]

[26] Many of the continuous variables have a skewed distribution and transforming to logs is one way to help stabilize the variances. The energy services (NMEALS, NDISHWCY, NWASHING, NENTT), the energy literacy index (ENLIT) and the energy consumption behaviour (BEHAV) can take a minimum value of zero (Tables 2 and 3). These variables were first transformed by adding 1 to all sample points, i.e. $\{0, 1, 2, \ldots, 11\} \longmapsto \{1, 2, 3, \ldots, 12\}$, and then log is taken. This should not be of too much of a concern here as we are interested in the relative measure and not on the absolute values. As a robustness check we also estimated the model without taking logs on these count variables and also taking a square root transformation instead of logs. The obtained efficiency estimates were found to be very similar.

[27] The weak (or non-) significance of income may be due to the income effect being captured by some residential and household characteristics like the number of rooms and household size. We estimated a simple model with only the price of electricity, income, regional dummies and a time trend. The results show that in this simple model income is positive and significant.

[28] We perform some robustness checks by estimating several models: (i) including HDD but no CDD; (ii) including CDD but no HDD; (iii) using total degree days (DD) that is the sum of HDD and CDD; and (iv) including both HDD and CDD but no regional dummies. In all these cases, we find the coefficient (respectively) on HDD, CDD, DD, and both HDD and CDD to be positive and significant. We also found the estimates and efficiency values to be very similar.

[29] It needs to be stated that, in the literature on stochastic frontier analysis, it is possible to find econometric models that assume that the energy and investment literacy variables explain the level of efficiency in the use of electricity instead of directly the demand for electricity as in Eq. (1). This would mean that the one-sided error terms h_i and u_{it} are functions of ENLIT and INVLIT. Unfortunately, such an estimation strategy within the econometric approach proposed by Filippini and Greene (2016) is relatively complicated and currently it is not implemented for GTREM. As a robustness check, we decided to estimate Eq. (1) using some econometric models that do not distinguish between the two components of inefficiency (transient and persistent) but allow the level of inefficiency to be a function of ENLIT and INVLIT. For this purpose, we decided to use the REM, Battese and Coelli (Battese and Coelli, 1995), and TREM; both energy and investment literacy were found to be significant in explaining the level of efficiency.

[30] For comparison, we also estimated the model using older approaches (REM and TREM) discussed in Section 3.1. The results are included in Tables 9 and 10 in the Appendix. As expected the efficiency levels from TREM are highly correlated with those from the transient efficiency from GTREM (correlation = 0.931). The persistent efficiency levels from GTREM exhibit a lower correlation with REM estimates (correlation = 0.397). Furthermore, REM estimates of efficiency levels are much lower than those of TREM and GTREM since REM regards any time-invariant and group specific unobserved heterogeneity as inefficiency.

Table 4
Estimation results.

	GTREM-1		GTREM-2	
	Coefficient	Std. error	Coefficient	Std. error
(Log) price of electricity	−0.3032***	(0.037)	−0.2882***	(0.037)
Single family household	0.1674***	(0.007)	0.2305***	(0.007)
(Log) household size	0.3472***	(0.011)	0.4338***	(0.011)
(Log) dwelling size in m^2	0.3921***	(0.009)	0.4778***	(0.009)
Has young people	−0.0449***	(0.008)	0.0011	(0.008)
Has elderly people	0.0346***	(0.006)	0.0215***	(0.006)
Income in 6k–12k	−0.0119**	(0.006)	−0.0090	(0.006)
Income above 12k	−0.0180**	(0.009)	−0.0134	(0.009)
Built in 1940–1970	−0.0773***	(0.008)	−0.0736***	(0.008)
Built in 1970–2000	0.0440***	(0.007)	0.1076***	(0.007)
Built in 2000–2015	−0.0558***	(0.009)	0.0408***	(0.009)
Minergie house	0.0185*	(0.010)	0.0633***	(0.010)
Absent 5 to 8 weeks/year	−0.1506***	(0.009)	−0.1526***	(0.009)
Has 2nd fridge	0.1042***	(0.007)	0.1494***	(0.007)
Has separate freezer	0.1126***	(0.005)	0.1481***	(0.005)
No special appliances	−0.0767***	(0.006)	−0.0858***	(0.006)
(Log) number of cooked meals	0.0021	(0.006)	–	–
(Log) dishwashing cycles	0.1151***	(0.004)	–	–
(Log) cloth washing/drying cycles	0.1009***	(0.004)	–	–
(Log) hours of tv/pc	0.1708***	(0.004)	–	–
Cooks using electricity	0.0957***	(0.008)	0.1598***	(0.008)
(Log) heating degree days	−0.1051	(0.111)	−0.0777	(0.110)
(Log) cooling degree days	0.1923***	(0.046)	0.1717***	(0.046)
Region = Aarau	0.0559***	(0.020)	0.0314	(0.020)
Region = Winterthur	−0.1312***	(0.040)	−0.0879**	(0.040)
Region = Biel/Bienne	0.0768***	(0.024)	0.0396	(0.024)
Region = Lucerne	−0.0514***	(0.017)	−0.0846***	(0.017)
Region = Bellinzona	−0.2524***	(0.066)	−0.2864***	(0.065)
University degree	−0.0144***	(0.006)	−0.0434***	(0.006)
University degree (partner)	−0.0185***	(0.007)	−0.0088	(0.007)
(Log) energy saving behaviour	−0.0227***	(0.007)	−0.0412***	(0.007)
(Log) energy literacy index	−0.0126***	(0.004)	−0.0157***	(0.004)
Investment literacy	−0.1137***	(0.006)	−0.1109***	(0.006)
Time trend (linear)	−0.1190***	(0.022)	−0.1072***	(0.022)
Time trend (quadratic)	0.0230***	(0.004)	0.0213***	(0.004)
α	5.6722***	(0.719)	5.5717***	(0.713)
σ_w	0.3960***	(0.002)	0.4228***	(0.002)
$\sigma_{(\nu+u)}$	0.2542***	(0.003)	0.2894***	(0.003)
λ	0.7553***	(0.041)	1.2193***	(0.041)
σ_h	0.5411***	(0.017)	0.2696***	(0.014)
Observations:	8295		8295	
Log-likelihood:	−1735.7		−1867.4	

***, **, * ⇒ Significance at 1%, 5%, 10% levels.

In GTREM-1, the short-run or the transient part of the efficiency in residential electricity consumption is found to be between 63.4% and 97.4%, with a mean value of about 89.2%. The long-run component representing the persistent part of the efficiency ranges from 39.4% to 84.1% and has a mean value of 78.4%.

In GTREM-2, which is a more traditional SFA model without any energy services, the mean level of transient efficiency is observed to be at 84.8%, and the level of persistent efficiency at 84.0%. Persistent efficiency is observed to be lower both in terms of the mean value and the variance in both specifications, implying higher long-run inefficiencies. This high value of inefficiency is indicative of structural problems faced by Swiss households, who probably rely on an old appliance stock within their homes. Moreover, this also possibly points to systematic behavioral shortcomings in terms of consumption of energy services.

The efficiency levels presented above indicate that there is a significant potential for the Swiss residential sector in the urban and sub-urban areas to save energy. In fact, households could save as much as 22% of their electricity usage in the long-run if they could improve on systematic and structural inefficiencies. With the reduction of transient inefficiencies in the short-run, the potential to save electricity is up to 11%.

Table 5
Efficiency scores (transient and persistent).

Efficiency type	Median	Mean	Std. dev.	Minimum	Maximum
GTREM-1 (with energy services)					
Transient	0.894	0.892	0.026	0.634	0.974
Persistent	0.785	0.784	0.013	0.394	0.841
GTREM-2 (without energy services)					
Transient	0.856	0.848	0.051	0.395	0.966
Persistent	0.841	0.840	0.006	0.675	0.951

5.2. Level of efficiency conditional on investment literacy

In the context of residential electricity demand and given the discussion on stochastic frontier models, it is interesting to note that one could identify several frontiers. For example, structural frontiers may exist based on building-age wherein dwellings built in two different time-periods represent different reference frontiers.

Similarly, considering the level of investment literacy in our specification which is represented by a dummy, one could identify two distinct best practice frontiers – with, and without high investment literacy. The efficiency values given by the estimation is conditional on their respective best practice frontiers (*net efficiency* or *conditional efficiency*). Moreover, the inefficiency resulting as a consequence of the distance between the two frontiers can be measured by the coefficient on the dummy variable capturing investment literacy which indicates the difference in the level of efficiency in the use of electricity given the level of investment literacy.[31] Given the *net efficiencies* and the coefficient on the dummy variable, one can obtain a measure of *gross efficiencies* or *unconditional efficiencies* by comparing every household to the most favorable frontier (Coelli et al., 1999).

Table 6 shows the mean unconditional and conditional efficiency levels for both GTREM specifications. The two efficiency levels can give policymakers a hint as to if they can try to reduce a part of the unconditional inefficiency by targeting policies on a particular aspect, which in this context is investment literacy as we focus on conditional efficiencies subject to investment literacy. We notice that the unconditional efficiency levels are seen to be significantly lower which emphasizes the role played by investment literacy in defining the level of efficiency in the use of electricity.

Table 6
Mean efficiency conditional on investment literacy.

	GTREM-1		GTREM-2	
	Net-eff	Gross-eff	Net-eff	Gross-eff
Transient	0.892	0.796	0.848	0.759
Persistent	0.784	0.700	0.840	0.752

6. Conclusions

A household's energy demand is not a demand for energy per se but a derived demand for energy services, such as cooling, heating, cooking and lighting. A reduction in energy consumption for the production of a given level of energy services can be achieved by either improving the level of efficiency in the use of inputs (i.e. in the use of appliances), by adopting a new energy-saving technology (i.e. purchase of new appliances, investments in energy-saving renovations) or by both processes. Technological change can induce a reduction of energy consumption for a given level of energy services, provided that the inputs are used in an efficient way, i.e. given that the households are productively efficient. The total reduction in residential energy consumption is therefore a result of the interplay of technological change and a household's behavior.

To measure this inefficiency in the use of electricity in Swiss households, we estimate a stochastic frontier model for residential electricity demand. We use data from a Swiss household survey conducted in 2015 that collected panel data over five years. The dataset includes information on the level of energy services, which is crucial, but often difficult to measure. The newly developed generalized true random effects model (GTREM) is used to estimate the transient and persistent levels of efficiency in the use of electricity. This study contributes to the literature on efficiency measurement by highlighting the importance of the distinction between the two types of efficiencies. Our unique panel dataset includes information on the level of energy services, which is usually not measured but critical for the application of SFA. In addition, we analyze the impact of energy and investment literacy on the total electricity consumption of households while controlling for the effects of education of the household members. Our results therefore provide new insights into the interrelations between the literacy and education variables and their role for transient and persistent efficiency in residential electricity consumption. The median persistent inefficiency is found to be around 22% whereas the transient inefficiency is seen around 11%. These results suggest that there is a considerable potential for saving electricity and thus reaching the reduction target defined by the Swiss federal council as part of the *Energy Strategy 2050*.

We further investigate if energy literacy, investment literacy and energy-saving behavior have an influence on the household electricity consumption. We construct a score on energy literacy, a binary variable for investment literacy, and an index that aggregates several energy saving behaviors and include these in our GTREM specification. The results show that for households exhibiting energy saving behavior, electricity consumption is seen to be lower. Similarly, households possessing a higher energy literacy and, in particular, investment literacy are also associated with lower electricity consumption.

From the point of view of policy makers, we note that the high persistent inefficiency is indicative of structural problems faced by households and systematic behavioral shortcomings in residential electricity consumption. The results presented here indicate a positive role of energy literacy, investment literacy and energy-saving behavior in reducing household electricity consumption and perhaps addresses part of the systematic behavioral failure exhibited by households. Policies that target an improvement of energy literacy, investment literacy and promote energy-saving behavior among the Swiss population could help to enhance the efficiency in the use of energy within households, which could prove beneficial in the long run. Finally, we emphasize again that clear distinction has to be made between the persistent and transient inefficiencies faced by households in order to appropriately channel the relevant policy measures. For instance, energy policy measures that try to promote energy saving (such as an information campaign) or try to increase the level of energy literacy (such as distribution of information leaflets and booklets among households) will probably have an impact on the level of transient efficiency. On the other hand, policy measures that try to improve the level of investment literacy, such as short courses that train individuals in assessing investments or web-pages and mobile-apps that help to calculate the life-cycle cost of appliances, could have an impact on the buying process of appliances, and therefore, on the level of persistent efficiency.

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[31] Of course, we are aware that it could be interesting to estimate the level of efficiency in the use of electricity conditional on the level of energy literacy. However, due to the fact that the level of energy literacy is not measured with a dummy variable, the definition of the reference frontier is not straightforward.

Appendix A

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)

Fig. 1. Energy-related literacy question on the price of 1 kWh of electricity.

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 60ºC)	◯	◯	◯	◯	◯	◯	◯

Fig. 2. Energy-related 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 60ºC
- ◯ 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:

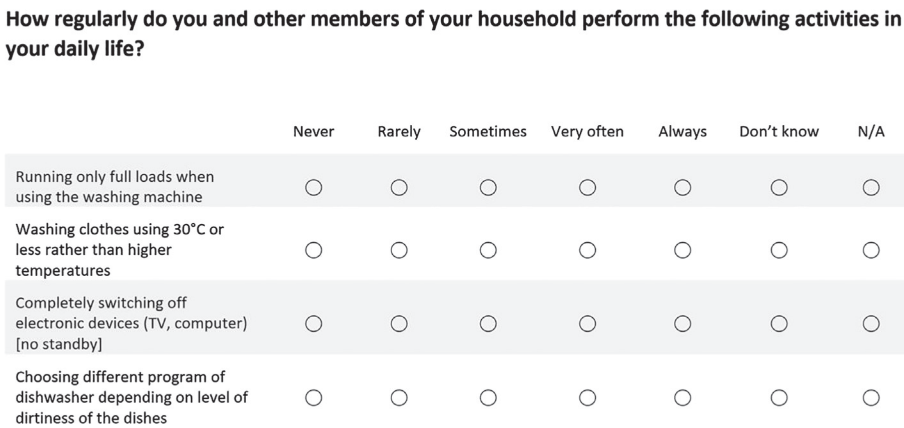
- ◯ Running a desktop PC for 1 hour
- ◯ Running a laptop for 1 hour
- ◯ Both consume about the same
- ◯ Don't know

Fig. 3. Energy-related literacy questions on comparison of electricity consumption of appliances.

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

Fig. 4. Survey question on mathematical/investment literacy.



How regularly do you and other members of your household perform the following activities in your daily life?

	Never	Rarely	Sometimes	Very often	Always	Don't know	N/A
Running only full loads when using the washing machine	○	○	○	○	○	○	○
Washing clothes using 30°C or less rather than higher temperatures	○	○	○	○	○	○	○
Completely switching off electronic devices (TV, computer) [no standby]	○	○	○	○	○	○	○
Choosing different program of dishwasher depending on level of dirtiness of the dishes	○	○	○	○	○	○	○

Fig. 5. Survey questions on energy-saving behaviour.

Table 7
Comparison of basic demographic characteristics of the six urban areas.

	Biel/Bienne		Lucerne		Bellinzona		Lugano		Winterthur		Aarau	
	Sample (N=877)	SSV	Sample (N=1375)	SSV	Sample (N=583)	SSV	Sample (N=1406)	SSV	Sample (N=739)	SSV	Sample (N=826)	SSV
Share of females (%)	52.61	51.19	51.39	52.07	51.06	52.88	51.69	51.85	50.35	50.91	50.35	51.13
Share of population by age (%)												
Young (0–19 years)	17.15	19.09	13.08	15.66	25.96	18.48	20.04	17.57	20.44	19.69	19.11	16.86
Adult (20–64 years)	62.04	62.21	63.82	64.93	62.25	60.77	63.24	60.68	65.11	64.05	58.92	64.72
Elderly (65+ years)	20.81	18.69	23.10	19.41	11.79	20.75	16.72	21.75	14.45	16.26	21.97	18.42
Mean household size	2.18	2.10	2.09	1.90	2.60	2.10	2.40	2.00	2.31	2.20	2.43	2.00
Dwelling (mean values)												
Living space per head (m^2)	51.63	38.00	52.44	45.00	52.62	44.00	54.19	46.00	49.10	43.00	62.36	48.00
People per room	0.57	0.66	0.57	0.58	0.65	0.61	0.63	0.62	0.61	0.61	0.53	0.55

Data at city level from 2015.
Data source: Swiss cities association (Schweizerischer Städteverband/SSV).

Table 8
Descriptive statistics over 2010–2014 (unbalanced panel of 1994 households).

Households →	Year = 2010 (1065)		Year = 2011 (1568)		Year = 2012 (1729)		Year = 2013 (1972)		Year = 2014 (1961)	
	Mean	Std.dev.	Mean	Std.dev.	Mean	Std.dev.	Mean	Std.dev.	Mean	Std.dev.
Q_E	3629.26	2467.77	3136.85	2270.76	3002.00	2360.20	3130.14	2331.90	2935.53	2214.20
MP_AVG	17.84	2.66	19.00	2.52	18.65	2.78	18.42	2.29	19.17	2.02
HHSIZE	2.57	1.29	2.42	1.20	2.36	1.18	2.30	1.16	2.28	1.14
INC6K	0.30	0.46	0.30	0.46	0.30	0.46	0.30	0.46	0.30	0.46
INC6_12K	0.52	0.50	0.52	0.50	0.52	0.50	0.51	0.50	0.51	0.50
INC12K	0.18	0.38	0.18	0.38	0.18	0.39	0.18	0.39	0.19	0.39
HDD	3310.85	302.85	2779.06	196.58	3046.15	272.51	3191.46	342.13	2562.07	240.46
CDD	209.81	82.45	170.47	79.66	200.37	98.00	215.88	70.59	106.00	44.36
IS_SFH	0.38	0.49	0.30	0.46	0.29	0.45	0.27	0.44	0.27	0.44
SQM	129.92	56.45	123.55	54.48	122.60	54.54	120.36	53.54	120.49	53.67
BLT1940	0.19	0.39	0.19	0.39	0.19	0.39	0.18	0.39	0.18	0.39
BLT1970	0.25	0.44	0.27	0.44	0.26	0.44	0.27	0.44	0.27	0.44
BLT2000	0.41	0.49	0.38	0.49	0.37	0.48	0.36	0.48	0.36	0.48
BLT2015	0.15	0.36	0.15	0.36	0.18	0.38	0.19	0.39	0.19	0.39
MINERGIE	0.06	0.23	0.06	0.24	0.07	0.26	0.08	0.28	0.08	0.28
WABS5TO8	0.08	0.27	0.08	0.27	0.08	0.27	0.08	0.27	0.08	0.27
HAS_FR2	0.22	0.41	0.20	0.40	0.19	0.39	0.18	0.38	0.18	0.38
HAS_FREE	0.59	0.49	0.54	0.50	0.52	0.50	0.50	0.50	0.50	0.50
NONE_APP	0.63	0.48	0.69	0.46	0.69	0.46	0.70	0.46	0.70	0.46
COOKEL	0.89	0.31	0.89	0.31	0.89	0.31	0.90	0.30	0.90	0.30
LUG	0.34	0.48	0.26	0.44	0.25	0.43	0.25	0.43	0.25	0.43
AAR	0.14	0.35	0.10	0.31	0.11	0.31	0.11	0.31	0.10	0.31
WINT	0.16	0.37	0.12	0.33	0.13	0.33	0.13	0.33	0.13	0.33
BIEL	0.25	0.44	0.18	0.38	0.18	0.38	0.16	0.37	0.17	0.37
LUZ	–	–	0.26	0.44	0.26	0.44	0.28	0.45	0.28	0.45
BELL	0.10	0.30	0.07	0.26	0.08	0.26	0.08	0.27	0.08	0.28
UNIV	0.34	0.48	0.35	0.48	0.36	0.48	0.38	0.48	0.37	0.48
UNIV_PAR	0.15	0.36	0.16	0.37	0.17	0.38	0.18	0.39	0.18	0.39

Table 9
Comparison of estimation results with older methods.

	REM		TREM		GTREM	
	Estimate	t ratio	Estimate	t ratio	Estimate	t ratio
LNP_E	−0.1848	−3.25	−0.3250	−9.19	−0.3032	−8.31
IS_SFH	0.1718	9.09	0.1561	21.96	0.1674	23.03
LN_HS	0.4131	21.89	0.3433	31.63	0.3472	31.26
LN_SQM	0.3086	13.82	0.3654	41.95	0.3921	44.40
HAS_YOUN	−0.0969	−5.08	−0.0479	−6.13	−0.0449	−5.66
HAS_ELDE	−0.0053	−0.37	0.0383	6.79	0.0346	5.98
INC6_12K	−0.0017	−0.14	−0.0103	−1.74	−0.0119	−2.01
INC12K	−0.0032	−0.18	−0.0158	−1.83	−0.0180	−2.07
BLT1970	0.0267	1.57	−0.0684	−9.02	−0.0773	−10.06
BLT2000	0.1163	6.62	0.0665	9.24	0.0440	5.99
BLT2015	0.1007	4.12	−0.0459	−5.08	−0.0558	−6.15
MINERGIE	0.0636	2.27	0.0299	2.97	0.0185	1.83
WABS5TO8	−0.1536	−7.78	−0.1221	−13.80	−0.1506	−16.89
HAS_FR2	0.0871	6.02	0.0912	13.83	0.1042	15.48
HAS_FREE	0.1421	10.46	0.1263	23.69	0.1126	20.63
NONE_APP	−0.0790	−6.06	−0.0661	−11.88	−0.0767	−13.46
LNMEALS	0.0502	3.16	0.0072	1.18	0.0021	0.35
LNDISH	0.1490	12.56	0.1325	32.37	0.1151	28.06
LNWASHIN	0.1162	12.87	0.1115	32.31	0.1009	28.58
LNENTT	0.1318	10.07	0.1566	37.49	0.1708	40.58
COOKEL	0.1332	7.11	0.1263	15.40	0.0957	11.44
LNHDD	−0.0934	−0.80	−0.1742	−1.59	−0.1051	−0.95
LNCDD	0.2009	4.14	0.2263	4.92	0.1923	4.15
AAR	0.1793	6.01	0.0455	2.35	0.0559	2.85
WINT	0.0003	0.01	−0.1850	−4.67	−0.1312	−3.29
BIEL	0.0741	2.24	0.0854	3.55	0.0768	3.16
LUZ	0.0974	3.96	−0.0487	−2.97	−0.0514	−3.09
BELL	−0.2005	−2.65	−0.3043	−4.65	−0.2524	−3.85
UNIV	−0.0429	−3.42	−0.0413	−7.56	−0.0144	−2.60
UNIV_PAR	−0.0968	−6.55	0.0092	1.36	−0.0185	−2.69
LNBEHAV	−0.0934	−5.55	−0.0281	−4.29	−0.0227	−3.39
LNENLIT2	−0.0093	−0.92	−0.0085	−2.16	−0.0126	−3.20
INVLIT	−0.0651	−4.72	−0.1231	−23.11	−0.1137	−20.57
T	−0.1216	−5.14	−0.1317	−6.00	−0.1190	−5.30
T*T	0.0236	5.95	0.0253	6.86	0.0230	6.11
α	4.9545	6.24	6.4229	8.79	5.6722	7.89
λ	3.0095	29.07	0.1200	0.20	0.7553	18.47
σ_u	0.6670	53.16	–	–	–	–
σ_w	–	–	0.4002	174.42	0.3960	165.44
$\sigma_{(v+u)}$	–	–	0.2185	21.53	0.2542	87.09
σ_h	–	–	–	–	0.5411	31.83
Observations:	8295		8295		8295	
Log-likelihood	−1708.60		−1654.91		−1735.77	

Table 10
Comparison of efficiencies.

	Median	Mean	Std. Dev.	Minimum	Maximum
REM	0.585	0.595	0.185	0.049	0.987
TREM	0.979	0.979	0.001	0.968	0.988
GTREM (Transient)	0.894	0.892	0.026	0.634	0.974
GTREM (Persistent)	0.785	0.784	0.013	0.394	0.841

Correlation between TREM and GTREM (Transient) = 0.931.
Correlation between REM and GTREM (Persistent) = 0.397.

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