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Determining the efficiency of residential electricity consumption

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Abstract

Increasing energy efficiency is a key global policy goal for climate protection. An important step toward an optimal reduction of energy consumption is the identification of energy saving potentials in different sectors and the best strategies for increasing efficiency. This paper analyzes these potentials in the household sector by estimating the degree of inefficiency in the use of electricity and its determinants. Using stochastic frontier analysis and disaggregated household data, we estimate an input requirement function and inefficiency on a sample of 2000 German households. Our results suggest that the mean inefficiency amounts to around 20%, indicating a notable potential for energy savings. Moreover, we find that household size and income are among the main determinants of individual inefficiency. This information can be used to increase the cost-efficiency of programs aimed to enhance energy efficiency.

Keywords Household electricity consumption · Stochastic frontier analysis · Technical efficiency

JEL Classification D1 · Q4 · Q5

1 Introduction

Global energy consumption is projected to grow by 25% until 2040, implying rising greenhouse gas (GHG) emissions (IEA 2019, p. 35). To mitigate GHG emissions,

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fostering energy efficiency has become a major political goal in many countries. For instance, the European Union (EU) started to set energy efficiency targets in 2006, enacting an action plan that aimed at reducing the consumption of primary energy by 20% by 2020 compared to 1990 levels. Specifically, EU member states were required to set individual reduction targets and report on these regularly. More recently, a new target for 2030 was stipulated, which aims at reducing energy use by 32.5% (EU 2020) relative to a business as usual scenario. In addition, the EU has launched several initiatives to fulfill these targets, including, for instance, standards for energy-using products (Houde and Spurlock 2016), regulations for buildings (Frondel et al. 2020), and mandatory energy labels for electric appliances (Andor et al. 2020; Houde 2018).

In order to develop cost-efficient strategies for energy saving, it is helpful to estimate the saving potentials in the different sectors. If there is a substantial potential for energy savings in a sector, the question arises as to how energy efficiency can be optimally increased. A low rate of energy efficiency in the residential sector may have two different causes: First, consumers might hesitate to purchase energy-efficient technologies, even though they pay off. For this so-called energy-efficiency-gap (Jaffe and Stavins 1994), many explanations have been provided in the literature, such as imperfect information, inattention, and biased beliefs (Allcott and Greenstone 2012; Gerarden et al. 2017). Second, given the appliance stock, households might use it inefficiently, for instance, by not switching the light off when absent from home.

In this paper, we aim to both measure the level and identify the determinants of inefficiency in the use of residential electricity. For this purpose, we use survey data on about 2000 households in Germany comprising electricity consumption levels, detailed information on the appliance stock and utilization, as well as socioeconomic characteristics. We are the first to conduct such a study in Germany, which presents a special case, as it has decided to phase out nuclear power by 2022 and coal power by 2038. At the same time, the deployment of renewable energy sources is drastically expanding and also ambitious targets for energy consumption have been set. For instance, by 2050, the German government aims to reduce electricity consumption by 50% in comparison with the level in 2008 (BMW 2018).¹

We estimate inefficiency by employing stochastic frontier analysis (SFA) methods. Furthermore, we allow for personal characteristics to influence the efficiency level, providing insights into who are the less efficient households. This information can be used to target policies on households that have the greatest potential for increasing efficiency and ultimately reducing energy consumption. This in turn could lead to more cost-effective policies and lower greenhouse gas emissions (see, e.g., Gillingham et al. 2018; Allcott and Greenstone 2012).

The econometric methods of estimating efficiency can roughly be divided into parametric and nonparametric kinds of approaches (see, for instance, Andor and Hesse 2014; Andor et al. 2019 and Parmeter and Zelenyuk 2019). Both make use of economic production theory and aim to identify potentials of increasing output given a set of inputs. This is achieved by estimating a production frontier and benchmarking between units (or entities of production) to gain knowledge about technical and rela-

¹ Ringel et al. (2016) provide a more comprehensive review of energy policy in Germany and analyze its socioeconomic impacts.

tive efficiency. The theoretical foundations for the parametric approach of stochastic frontier analysis (SFA) used in this paper have been laid by Aigner et al. (1977) and Meeusen and van den Broeck (1977).

The literature on the efficient use of energy initially focused on the economic theory of production using aggregate data (for an overview, see our literature review in Sect. 2 and Filippini and Hunt 2015). More recently, scholars make use of disaggregated data. For instance, Alberini and Filippini (2018) estimate the technical efficiency in the use of electricity using data on US households. In addition, the recent literature (e.g., Blasch et al. 2017; Boogen 2017; Broadstock et al. 2016; Weyman-Jones et al. 2015) also considers the role of determinants of (in)efficiency since residential consumers are typically very heterogeneous in various dimensions, such as lifestyle and household size, income, as well as the number and utilization of electric appliances.

We identify determinants of inefficiency (contrasting, e.g., Alberini and Filippini 2018), which allows us to draw policy conclusions that were not possible with previous study approaches. In particular, we use micro-level data (contrasting Orea et al. 2015) and consider a larger suite of both energy services and determinants of inefficiency than, for instance, Weyman-Jones et al. (2015) and Broadstock et al. (2016). Moreover, we explicitly model inefficiency in the consumption of electricity rather than assuming that its determinants, such as gender and education, have a direct bearing on the electricity consumption (compared to Boogen 2017 and Blasch et al. 2017).

In our view, it is crucial to consider the determinants of individual inefficiency because the mere knowledge about the existence of inefficiency in residential electricity consumption does not allow any inference on how to reduce it. The impact of individual characteristics on inefficient energy consumption can inform various stakeholders. For instance, governments and companies concerned with reducing greenhouse gas emissions might advance policies that nudge consumers to a more efficient use of appliances or entail financial rewards (List et al. 2017). Moreover, better informed consumers can reduce their energy costs by conditioning on a larger information set.

Our results suggest that the mean inefficiency in German residential electricity consumption is around 20%. Thus, there is a considerable potential for improving the energy efficiency. Moreover, we find that smaller households, low-income households, tenants, and households living in multiple-family homes tend to use electricity less efficiently. Hence, targeting these households with energy efficiency programs, such as energy audits and information campaigns, might improve their cost-effectiveness and maximize the reduction of electricity consumption and related GHG emissions. While the existing literature recommends targeting in particular households with high electricity consumption levels (for instance, Allcott 2011 and Andor et al. 2020), our findings thus suggest additional criteria for targeting.

The subsequent section provides a literature review, and Sect. 3 explains the data for our analysis. Section 4 describes the methodology, and Sect. 5 presents our results. The last section summarizes and concludes.

2 Background

While increasing energy efficiency is a political goal in many countries around the world, there is no unique definition of what exactly “energy efficiency” is and how to measure and monitor it (for a discussion, see Filippini and Hunt 2015). Without a clear definition, it is also difficult to evaluate the effects of energy efficiency policies. In the past, the most considered indicator was energy intensity, typically defined as energy consumption per square meter at the household level or the ratio of energy consumption to GDP. However, many have criticized this indicator (see, for instance, IEA 2009, Evans et al. 2013), particularly because energy intensity does not directly measure the “true” energy efficiency. For example, the indicator can substantially vary just because the GDP suddenly decreases, e.g., due to a financial crises or a pandemic.

More recently, economists have proposed other approaches to define and estimate energy efficiency from an economics perspective Filippini and Hunt (2015). In particular, the different approaches measure the level of the efficient use of energy based on the economic theory of production and use empirical methods. To this end, Filippini and Hunt (2015) propose to measure energy efficiency econometrically by estimating a demand function for energy. Consequently, the difference between the optimal amount of energy, which corresponds to the cost minimizing input combination to produce a given level of energy services, and the observed amount of energy reflects the level of energy inefficiency.

As there is a long history of research on the production and efficiency analysis, several methods have already been developed, for instance, the classic nonparametric data envelopment analysis (DEA) and the parametric stochastic frontier analysis (SFA) (for a review of these two methods, see Andor and Hesse 2014; Andor et al. 2019 and Parmeter and Zelenyuk 2019). Filippini and Hunt (2015, p. 58) argue that economic approaches “are a sounder basis for measuring energy efficiency based on economic foundations rather than relying on simple energy intensity indicators.”

In the following, we briefly summarize the received literature on economic approaches to estimate energy efficiency based on efficiency analysis methods. Specifically, we provide an overview of empirical studies that estimate the level of efficiency in the use of energy (see Table 1). These studies can be further categorized by the specific sector analyzed, the kind of data, and whether studies consider determinants of inefficiency, i.e., $u = f(\delta, z)$.

One strand of the literature on the nexus of energy efficiency and the application of efficiency methods involves the use of aggregate data. For instance, Filippini and Hunt (2011), Evans et al. (2013), and Zhou et al. (2012) determine energy efficiency measures of whole economies in OECD countries, while Borozan (2018), Saussay et al. (2012), and Filippini et al. (2014) estimate efficiency across European countries. On a more regional level, (Wei et al. (2009)) as well as Filippini and Zhang (2016) estimate energy efficiency for Chinese provinces, whereas Filippini and Hunt (2012) and Orea et al. (2015) analyze energy efficiency in US states.

Another strand of the literature employs disaggregated data. While there is some work on individual firms in the industry (see, e.g., Bernstein 2020; Boyd 2008; Lundgren et al. 2016 and Amjadi et al. 2018) and in the commercial sector (Buck and Young 2007), detailed data are also used in the residential sector. For instance, Grösche (2009)

Table 1 Literature review table—energy efficiency and determinants

Study	Unit	Location	Method	Data	Range	$u = f(\delta, z)$
Alberini and Filippini (2018)	Households	USA	SFA	Micro	Panel	
Bernstein (2020)	Electric power plants	USA	SFA	Micro	Panel	✓
Blasch et al. (2017)	Households	Switzerland	SFA	Micro	Panel	
Boyd (2008)	Manufacturing plants	USA	SFA	Micro	Panel	
Boogen (2017)	Households	Switzerland	SFA	Micro	Cross-section	
Borozan (2018)	Regional differences	Europe	DEA	Aggregate	Panel	✓
Broadstock et al. (2016)	Households	China	SFA	Micro	Cross-section	✓
Buck and Young (2007)	Commercial buildings	Canada	SFA	Micro	Cross-section	✓
Filippini and Hunt (2011)	Economies	OECD	SFA	Aggregate	Cross-section	
Filippini and Hunt (2012)	Households	USA	SFA	Aggregate	Panel	
Filippini et al. (2014)	Policies & households	EU	SFA	Aggregate	Panel	✓
Grösche (2009)	Single-family homes	USA	DEA	Micro	Cross-section	✓
Lundgren et al. (2016)	Industry	Sweden	SFA	Micro	Panel	✓
Orea et al. (2015)	Households & rebound	USA	SFA	Aggregate	Panel	✓
Otsuka (2017)	Households	Japan	SFA	Aggregate	Panel	✓
Saussay et al. (2012)	Policies & households	EU	SFA	Aggregate	Panel	✓
Weyman-Jones et al. (2015)	Households	Portugal	SFA	Micro	Cross-section	✓
Zhou et al. (2012)	Economies	OECD	SFA	Aggregate	Cross-section	

estimates energy efficiency of single-family homes in the USA between 1997 and 2001. Based on survey data on the appliance stock, Weyman-Jones et al. (2015) and Broadstock et al. (2016) estimate overall residential energy efficiency for Portuguese and Chinese households, respectively. Using efficiency methods on a sample of Swiss electricity customers, Boogen (2017) and Blasch et al. (2017) find that the level of inefficiency is within the range of 20–25%. Alberini and Filippini (2018) conduct a similar analysis for the USA and detect inefficiency levels of around 10%.

Since residential consumers are typically very heterogeneous in various dimensions, such as lifestyle, household size, and income, the recent literature in this domain has started to account for socio-demographic characteristics.² For instance, Otsuka (2017) estimates residential electricity efficiency scores of 47 prefectures in Japan and finds that efficiency increases with household size and floor size due to economies of scale. Using aggregate data on residential energy consumption, Orea et al. (2015) include economic determinants of the demand for energy services to estimate rebound effects.³ They find that the rebound effect declines with income and household size, while it increases with energy prices. In her analysis, Boogen (2017) accounts for housing characteristics as additional inputs to the energy appliance stock and utilization behavior. She detects, for instance, that urban households use electricity less efficiently, while households residing in single-family homes use electricity more efficiently. Blasch et al. (2017) focus on energy and financial literacy and find that energy consumption is lower among households with energy and financial literate heads.

This paper differs from the existing literature in that we use micro-level data (compared to Orea et al. 2015) and explicitly model determinants of inefficiency rather than excluding them (Alberini and Filippini 2018) or including them on the frontier itself (Blasch et al. 2017; Boogen 2017) to estimate the impact on consumption. Our view is that determinants of efficiency provide a helpful source of information to exploit and that the electricity usage frontier might not be directly impacted by, for example, the gender of a household head. Instead, systemic differences in how people deviate from the frontier manifest in model heterogeneity via determinants. Yet, as robustness checks, we also estimate models that consider the determinants on the frontier as well as on the frontier and the inefficiency term. What is more, our study is special in the sense that we are able to study various determinants of inefficiency, socio-demographics as well as the number and utilization of electric appliances. Thus, we extend the work by Weyman-Jones et al. (2015) and Otsuka (2017) who use a relatively simple model and by Broadstock et al. (2016) who focus on regional aspects.⁴

3 Data

To estimate the efficiency of residential electricity consumption, we draw on detailed household level data obtained from two surveys that were conducted by RWI—Leibniz Institute for Economic Research and the professional German survey institute *forsa*.⁵

² A comprehensive review of the research on both socio-demographic and psychological determinants of individual residential energy consumption is given by Frederiks et al. (2015). Mills and Schleich (2012) analyze the determinants for the demand of energy-efficient appliances.

³ The rebound effect denotes the idea that rising energy efficiency decreases the marginal cost of a certain energy service and in turn may increase the consumption of that (direct rebound) or other energy services (indirect rebound). For more information on the rebound effect and a review of relevant literature, see, e.g., Gillingham et al. (2016).

⁴ Another way to control for heterogeneity is the estimation of true random effects (TRE) and true fixed effects (TRF) models (Greene 2005; Chen et al. 2014) or of persistent inefficiency (Kumbhakar et al. 2014). Yet, all these models require a panel structure and are thus not feasible given our data set.

⁵ Specifically, RWI developed the questionnaires and commissioned *forsa* to carry out the data collection. Two of the authors (Mark A. Andor and S. Sommer) were part of the RWI team.

forsa collects data using a state-of-the-art tool that allows panelists to fill out the questionnaire either online or by using their television. Respondents—in our case household heads—retrieve and return questionnaires from home and can interrupt and continue the survey at any time. A large set of socioeconomic and demographic background information on all household members is available from *forsa*'s household selection procedure and updated regularly. The first survey is part of the German Residential Energy Survey (GRECS), which took place in early 2014, and gathered data on energy consumption and cost as well as on socioeconomic characteristics of 8561 households (RWI 2015).

Of those, 5220 households disclosed electricity billing information. We dropped 274 households with electric heating systems because their electricity consumption differs substantially from regular electricity customers and 321 outlier households (for details, see, Frondel et al. 2019).⁶ From the remaining households, we randomly selected about 2100 households for a second survey that followed in mid-2014. Its main purpose was to gather information on the households' electric appliance stock and its utilization.

Starting from 2106 observations, our estimation sample is reduced to 1638 due to the cumulation of item-nonresponses. Tables 2 and 3 document the summary statistics for our estimation sample. Table 2 shows that mean electricity consumption amounts to 3675 kilowatt-hours (kWh). Yet, electricity consumption is very heterogeneous, as indicated by the large standard deviation and the wide range from about 500 to more than 14,000 kWh. Moreover, the electricity consumption varies notably with respect to household size (Fig. 1). Not only is the consumption higher in larger households, but also the distribution becomes wider. Specifically, the distribution of electricity consumption exhibits the lowest variation for single-person households, while the spread is much larger for households with four and more members.

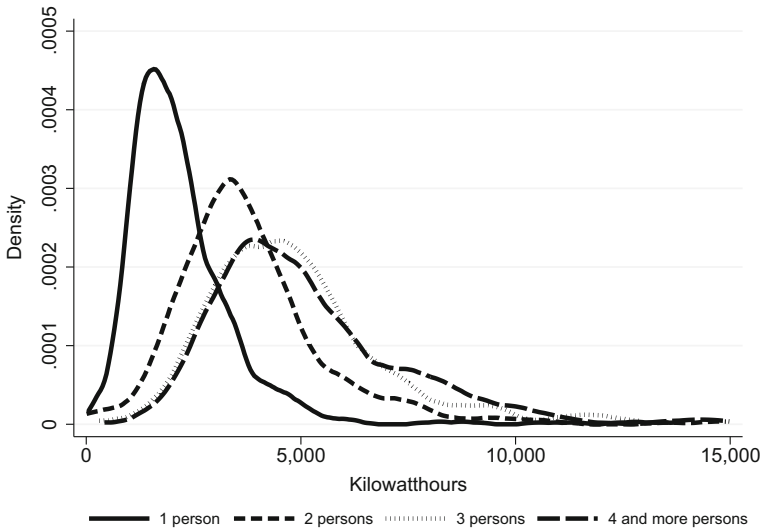
Table 2 furthermore summarizes socioeconomic characteristics. For example, with shares of about 30% and 43%, respectively, single- and two-person households represent the overwhelming majority of our sample, whereas households with three and more members are relatively rare. On average, respondents are 3.5 weeks absent from home, 58 years old,⁷ and have a monthly household net income of 2850 Euro. Around two-thirds of the respondents live in their own property, and slightly less than a third are women. This relatively low share of women could be due to the fact that we deliberately asked the household heads—defined as the person in a household that usually makes financial decisions at the household level—to complete the questionnaire. Furthermore, 44% of the respondents live in single-family homes, 17% in two-family

⁶ As electricity is not used for heating purposes among the households in our sample, we do not include variables about the quality of the dwelling, such as double glazing and property age.

⁷ Theoretically, the relatively high mean age could have practical implications, e.g., regarding the decision on investments in more energy-efficient appliances. Empirically, though, the relationship between age and investment decisions is not clear-cut: On the one hand, older household heads might be less likely to adopt energy-efficient technologies than younger household heads as the expected returns are lower. On the other hand, younger households are more likely to move and hence might be less inclined to adopt energy-efficient appliances (Mills and Schleich 2012).

Table 2 Summary statistics of socioeconomic characteristics

Variable	Mean	St. Dev.	Min	Max
Electricity consumption	3675	2026	521	14,816
1-person household	0.304	0.460	0	1
2-person household	0.427	0.495	0	1
3-person household	0.145	0.352	0	1
4+ person household	0.125	0.330	0	1
# Weeks absent from home	3.476	4.550	0	51
Age	57.9	12.7	19	87
East Germany	0.191	0.393	0	1
Income	2852	1286	700	5700
Homeowner	0.674	0.469	0	1
Female	0.299	0.458	0	1
Single-family home	0.447	0.497	0	1
Two-family home	0.175	0.380	0	1
Multiple-family home	0.379	0.485	0	1
Dwelling size	114.067	48.334	26	420
# Children	0.269	0.656	0	4

**Fig. 1** Electricity consumption for different household sizes

homes, and the remainder of 39% in buildings with multiple apartments. The average dwelling size amounts to $114m^2$.

Table 5 compares the characteristics of our sample to those of the population of German household heads and illustrates that our sample contains slightly less

Table 3 Summary statistics of household appliances

Variable	Mean	St. Dev.	Min	Max
# Refrigerators	1.440	1.020	0	18
# Freezers	0.741	0.708	0	9
Washing machine	0.976	0.153	0	1
# Washing cycles	186.817	149.939	13	1469
Dishwasher	0.838	0.368	0	1
# Dish washing cycles	152.603	123.207	0	832
Tumble dryer	0.565	0.496	0	1
# Drying cycles	55.643	90.052	0	1040
# TV sets	1.824	1.112	0	16
# PCs	1.958	1.196	0	9
# Light bulbs	25.451	16.016	0	170
# Meals	320.032	136.245	0	728
Water heating	0.165	0.371	0	1
Air-conditioning	0.004	0.065	0	1
Electric oven	0.946	0.226	0	1
Aquarium/terrarium	0.066	0.248	0	1
Waterbed	0.042	0.200	0	1
Sauna	0.076	0.266	0	1
Solarium	0.012	0.107	0	1
Pond pump	0.161	0.368	0	1

single-person households, while two-person households are slightly over-represented. Moreover, the respondents in our sample tend to be older compared to official data.

With respect to appliances, we gathered information on the ownership and their utilization (Table 3). Some major appliances, such as refrigerators and freezers, operate the whole day and permanently consume electricity. In such cases, we use information on the number of appliances available in a household, e.g., households have on average 1.4 refrigerators (# Refrigerators) and 0.7 freezers (# Freezers). For other major appliances, we elicited the utilization in the previous week or month and extrapolated it to the entire year. On average, households use the washing machine 187 times per year (# Washing cycles) and the dishwasher about every other day, in total 153 times per year (# Dish washing cycles). Tumble dryers are used only 57 times per year (# Drying cycles). The lower usage of dishwashers and tumble dryers is also due to a lower prevalence of these appliances: As our data indicate, 98% of the households have a washing machine, 84% have a dishwasher, and only 57% possess a tumble dryer (Table 3). We observe a large heterogeneity with respect to these variables: Some households report to run the washing machine up to four times per day and the dishwasher up to two times.

In general, gathering data on the utilization of some appliances may be prone to large uncertainties. Specifically, it is unlikely that a respondent of a multi-person household is able to disclose reliable information on the time spent watching television by all household members. Therefore, we employ the number of such appliances

that are present in a household, as the respondents might recollect this information more precisely than usage behavior. For instance, on average, households possess 1.8 televisions (# TV sets) and about two desktop PCs or laptops (# PCs).

Last, for less common appliances, such as air conditioning, aquariums and terrariums, waterbeds, saunas, and solariums, we only report whether the households own them. For instance, we observe that 16.5% of the households use electricity for water heating, while waterbeds are much less prevalent (4%), but almost every household has an electric oven (95%).

The appliances displayed in Table 3 undoubtedly represent only a limited set of all those electric devices that are typically available, but this selection should account for a large share of residential electricity consumption. To minimize the respondents' burden in filling out the questionnaire, we have deliberately refrained from asking about the total appliance stock, including appliances with rather low consumption rates, such as electric tooth brushes, water kettles, bread cutters, hoovers, and chargers.

4 Methodology

The literature on efficiency analysis can be roughly divided into the two branches of parametric and nonparametric approaches. Data envelopment analysis (DEA, Charnes et al. 1978) is the most widely applied nonparametric approach for efficiency analysis. It is quite flexible, but (in its standard form) does not consider statistical noise. In turn, stochastic frontier analysis (SFA, Aigner et al. 1977, Meeusen and van den Broeck 1977) methods take statistical noise into account and typically require assumptions regarding the functional form of the frontier and the distribution of the error term (for more details, see, for instance, Andor and Hesse 2014, Parmeter and Zelenyuk 2019).

As residential electricity consumption seems to be driven by a considerable degree of randomness, we decided to apply SFA (for a discussion of SFA approaches, see, for example, Parmeter and Kumbhakar 2014 and Andor and Parmeter 2017).

Filippini and Hunt (2015) compare three different models of applying SFA to electricity consumption: (1) Input requirement functions (Boyd 2008); (2) Shephard sub-vector distance functions that use an inefficiency term with a negative sign and a different specification of the dependent variable (Zhou et al. 2012); and (3) input demand frontier functions, which are identical to (1) except that they take input prices instead of quantities (Filippini and Hunt 2011).⁸ To estimate the efficiency level for residential electricity consumption, we specify an input requirement frontier function, which is given by:

$$\ln y_i = \alpha + \beta' \mathbf{x}_i + \varepsilon_i, \quad \text{with } \varepsilon_i = v_i + u_i \quad \text{for } i \in \{1, \dots, N\}, \quad (1)$$

where $\ln y_i$ is the log electricity consumption per m^2 for household i , \mathbf{x}_i is a vector of inputs, reflecting the households electric appliances and their utilization (Table 3), and β is a vector of the corresponding parameters. The error term ε_i is decomposed by $\varepsilon_i = v_i + u_i$ into two independent parts. v_i is a symmetric disturbance term

⁸ Theoretically, there is a fourth alternative approach proposed by Reinhard et al. (1999). Yet, this approach is rarely used (see, Filippini and Hunt 2015).

and captures stochastic noise (like the error term in an ordinary least square (OLS) model) and $u_i \geq 0$ is a one-sided error term, which indicates the level of inefficiency in the electricity consumption. This definition of the error terms constitutes the main distinction to the standard OLS method (Jondrow et al. 1982; Battese and Coelli 1988; Kumbhakar and Lovell 2000).

To give readers unfamiliar with efficiency analysis intuition, we briefly explain the general idea of SFA (see also, Andor and Hesse 2014). For the decomposition of the composed error term ε_i into the noise term v_i and the inefficiency term u_i , the skewness of the distribution of the error term ε_i is crucial. Inefficiency can only affect the dependent variable in one direction. In our case, inefficiency leads to more energy use than optimal, but it can never lead to less use than the optimal (minimal) use level. Therefore, the inefficiency distribution is skewed. By contrast, “randomness” can contribute positively or negatively and we expect by definition – analogously to the standard OLS case—that, on average, it is balanced. Therefore, it is plausible to assume a symmetric distribution with a zero mean for the noise term v_i . As the distribution of the composed error term ε_i is the combination of the distributions of u_i and v_i , it indicates the presence of inefficiency. The likelihood of inefficiency increases with the skewness of the distribution of ε_i . Using distributional assumptions for the noise term and the inefficiency term, SFA estimates the error term ε_i as well as the ratio of noise and inefficiency, by means of the method of moments, maximum likelihood or pseudo-maximum likelihood (Andor and Parmeter 2017).

Equation (1) represents the minimum electricity consumption of household i given a highly efficient appliance stock and its highly efficient utilization conditional on x_i , i.e., the frontier (abstracting from noise, $v_i = u_i = 0$). If a household is not on the frontier, the distance to it reflects the level of inefficiency in the use of electricity. Technical efficiency (TE, θ) provides a metric on the unit interval, which describes the percentage of electricity consumption not accounted for from the frontier, namely $\frac{y_i}{\beta'x_i}$, which is captured by the one-sided error term, u_i .

For our error specification, we estimate the classic normal half-normal (henceforth, NHN) model, i.e., $v_i \sim N(0, \sigma_v^2)$ and $u_i \sim |N(0, \sigma_u^2)|$ (Aigner et al. 1977). The NHN error distribution has the property that the efficiency scores are monotonic in the residual ε_i . Given this specification, we can estimate TE via the conditional expectation $\mathbb{E}[(e^{-u_i})|\varepsilon_i]$ (Jondrow et al. 1982). Formally, evidence of inefficiency can be tested via the existence of skewness in the OLS residuals.

There is evidence that households do not operate on the frontier due to disparities in personal characteristics and the appliance stock (Blasch et al. 2017; Boogen 2017). Therefore, we depart further from OLS and additionally allow for “determinants” of inefficiency z_i to impact the pre-truncation mean μ_i of the inefficiency term u_i via (Battese and Coelli 1995; Kumbhakar 1991):

$$\mu_i = \delta_0 + \delta'z_i \quad \text{for } i \in \{1, \dots, N\}, \tag{2}$$

where u_i is defined by the truncation of the normal distribution at zero with variance σ^2 . Hence, we have $u_i \sim |N(\mu_i, \sigma_u^2)|$. Positive coefficients on the right hand side of Equation (2) indicate that an increase in the corresponding variable is associated with increased inefficiency.

As an alternative, we allow for heterogeneous inefficiency by labeling the variance of the inefficiency term σ_u^2 as a function of “determinants” $\sigma_{u,i}^2 = \exp(\delta'z_i)$ (Caudill and Ford 1993). We refer to the former model as “NHN-Z μ ” and to the latter as “NHN-Z σ .” As determinants of the inefficiency, z_i , we use the socioeconomic characteristics reported in Table 2, for which δ is the corresponding parameter vector.⁹ Hence, compared to the existing literature (e.g., Blasch et al. 2017 and Boogen 2017), we explicitly model determinants of inefficiency rather than including them on the frontier itself. Our view is that the electricity usage frontier is not directly impacted by, for example, the gender of a household head. Instead, systemic differences in how people deviate from the frontier manifest in model heterogeneity via determinants. More succinctly, we segment our variables into factors that directly utilize electricity for the frontier and factors that may indirectly impact household electricity usage for inefficiency. Limitations pertaining to our model specification regarding which variables should be x 's and which should be z 's could be mitigated by a model selection algorithm, although we are unaware of such an algorithm within the SFA framework.¹⁰

Furthermore, rather than regressing the residuals of a first stage SFA regression without determinants on a set of determinants, this estimation procedure is carried out in one step.¹¹ The practice of allowing for determinants of inefficiency has two advantages. First, the determinants allow for Eq.(1) to have heteroscedasticity via u_i (e.g., Caudill and Ford 1993 and Caudill et al. 1995) and thus, this is a less restrictive model. Second, without determinants, providing policy recommendations is difficult as inefficiency is randomly determined. By contrast, because we include determinants, inefficiency is no longer random. Hence, based on the results, we can discuss ways of improving the energy efficiency of residential electricity consumption.

To avoid distributional assumptions on u_i and v_i , we deploy nonlinear least squares (NLS) as a robustness check (Wang and Schmidt 2002). Being that the NHN and NHN-Z σ models both have the scaling property, meaning that they can be written as the product of a scaling function and the basic distribution, NLS is a useful extension given the direct comparability (see also, Parmeter and Kumbhakar 2014). The NLS model is given by:¹²

$$\ln y_i = \alpha + \beta'x_i + v_i - \delta_0 e^{\delta'z_i}. \quad (3)$$

There is a trade-off between distributional assumptions and efficiency in using NLS versus maximum likelihood. Hence, if the NHN-Z σ specification is the correct func-

⁹ Orea et al. (2015) use a similar approach to estimate the rebound effect of energy consumption. Yet, we refrain from estimating rebound effects (thus assuming a zero rebound effect) as we lack data on marginal prices. Moreover, the findings of Chakravarty et al. (2013) and Davis (2008) suggest that the rebound effect is relatively modest for residential electricity consumption because of a low price elasticity and high saturation of electric appliances.

¹⁰ Therefore, we also estimate two alternative models where the determinants enter (i) on the frontier as well as (ii) on the frontier and via the inefficiency term as robustness checks (Table 9 in Appendix).

¹¹ For a discussion on one-step vs two-step estimation, see Andor and Parmeter 2017.

¹² Due to convergence failure of the NLS optimization algorithms, the constant (δ_0) was also exponentiated making it positive. This assumption is mitigated by the fact that in all other specifications herein, the inefficiency increases the dependent variable. In other words, inefficient households utilize more electricity than efficient ones.

tional form, we would expect the NLS standard errors to be larger than those on the NHN- $Z\sigma$ model.

5 Results

For our analysis, we consider electricity consumption per m^2 and take the logarithm to interpret the regression coefficients as semi-elasticities. Hence, we quantify the effect of each appliance or utilization to overall electricity consumption per m^2 as a change in percentages. To provide a benchmark for our analysis, we start with estimating the OLS version of Equation (1) without considering inefficiency, i.e., $u_i = 0$ (first column of Table 4). We find, for instance, that electric water heating increases electricity consumption by about 23%. Moreover, an aquarium or terrarium leads to an increase of electricity consumption by 16%. Furthermore, each use of a dishwasher increases consumption on average by 0.03%, whereas operating the tumble dryer consumes about twice as much electricity and thus increases electricity consumption by 0.05%. Given the mean electricity consumption figure (Table 2) and average usage, conditional on possessing the respective appliance (185 times for the dishwasher and 100 for the tumble dryer), we find that a dishwasher consumes on average 204 kWh and a tumble dryer 184 kWh per year.

Determining the skewness of the OLS residuals provides a formal test for the existence of inefficiency. In our application, the skewness of the residuals amounts to 0.159 and is statistically different from zero ($p < 0.000$), suggesting that there is a considerable level of inefficiency. In addition, the skewness of the residuals is a necessary condition for the convergence of the maximum likelihood function. The statistically significant coefficient for $\gamma = \frac{\sigma_u^2}{\sigma_v^2}$ also indicates that there is inefficiency in our data set (Column 2 of Table 4). Comparing the OLS result with the SFA estimation, in which we use a normal-half-normal (NHN) distribution for the composed error term, we note that the coefficients are fairly similar in magnitude, except for the constant since $E(\varepsilon_i) \neq 0$.

The last column of Table 4 shows the results of the SFA model (NHN- $Z\mu$) that additionally includes an estimation to identify the determinants of inefficiency in the electricity use.¹³ The higher value of the log likelihood indicates that the model fit is superior. While the coefficients for the frontier are similar to the model without determinants, we observe that, for instance, the household size and residing in East Germany are statistically significant determinants of inefficiency. For instance, the positive sign of the coefficient on *East Germany* indicates that East German households use electricity more inefficiently than households residing in West Germany.

The value for γ is notably larger, indicating that the degree of the residual explained by inefficiency increased after including determinants, as it commonly occurs in SFA. The reduction in significance of σ^2 in NHN- $Z\mu$ is not cause for concern given that both σ_v and σ_u are significant at the 0.001 and 0.01 levels, respectively. Furthermore, we observe that σ^2 increases, although the increase is entirely due to an increase in

¹³ The results of the specification where we model the variance of the inefficiency term as a function of determinants are shown in Appendix (Table 6) and are similar to the results presented in the main text.

Table 4 Estimation results

	OLS Coeff.	Std. Err.	NHN Coeff.	Std. Err.	NHN-Z μ Coeff.	Std. Err.
Frontier						
Water heating	0.233***	(0.029)	0.227***	(0.028)	0.210***	(0.029)
AC	-0.168	(0.160)	-0.195	(0.162)	-0.138	(0.154)
Electric oven	-0.041	(0.047)	-0.041	(0.046)	-0.016	(0.049)
Aquarium/terrarium	0.163***	(0.043)	0.163***	(0.042)	0.167***	(0.042)
Waterbed	0.093*	(0.053)	0.095*	(0.053)	0.087*	(0.052)
Sauna	-0.041	(0.040)	-0.043	(0.040)	-0.021	(0.040)
Solarium	-0.071	(0.099)	-0.070	(0.098)	-0.043	(0.093)
Pond pump	0.085**	(0.029)	0.087***	(0.029)	0.111***	(0.029)
Refrigerators	-0.014	(0.011)	-0.016	(0.011)	-0.016	(0.011)
Freezers	0.023	(0.016)	0.026	(0.016)	0.039**	(0.016)
Washing	0.0001	(0.0001)	0.0001	(0.0001)	0.0001*	(0.0001)
Dish washing	0.0003**	(0.0001)	0.0003***	(0.0001)	0.0004***	(0.0001)
Drying	0.0005***	(0.0001)	0.0005***	(0.0001)	0.001***	(0.000)
TVs	0.038***	(0.011)	0.037***	(0.011)	0.032***	(0.011)
PCs	0.011	(0.010)	0.010	(0.010)	0.013	(0.010)
Light bulbs	-0.003***	(0.001)	-0.003***	(0.001)	-0.002***	(0.001)
Meals	0.0003***	(0.0001)	0.0003***	(0.0001)	0.0003***	(0.0001)
Constant	3.189***	(0.055)	2.908***	(0.063)	2.916***	(0.060)
Absent	-	-	-	-	-0.120*	(0.072)
East Germany	-	-	-	-	0.235**	(0.115)
ln(Income)	-	-	-	-	-0.558	(0.347)
Homeowner	-	-	-	-	-0.650	(0.408)
Two-family home	-	-	-	-	1.037	(0.779)
Multiple-family home	-	-	-	-	1.172	(0.871)
Age	-	-	-	-	-0.014	(0.011)
Female	-	-	-	-	-0.436	(0.304)
Children	-	-	-	-	-0.437	(0.482)
2 persons household	-	-	-	-	1.029*	(0.608)
3 persons household	-	-	-	-	1.002*	(0.607)
4+ persons household	-	-	-	-	0.021	(0.727)
Constant	-	-	-	-	2.758**	(1.212)
σ^2	-	-	0.255***	(0.021)	0.596*	(0.336)
γ	-	-	0.487***	(0.075)	0.785***	(0.123)
$\bar{\theta}$	-	-	0.772***	(0.002)	0.831***	(0.002)
Log likelihood value	-	-	-898.6	-	-844.8	-
No. of observations	1,638	-	-	-	-	-

Standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The upper panel shows the results of Equation (1), while the lower panel shows the results of Equation (2). $\sigma^2 = \sigma_u^2 + \sigma_v^2$, $\gamma = \frac{\sigma_u^2}{\sigma_v^2}$, and θ is the mean efficiency score

σ_u with $\sigma^2 = \sigma_u^2 + \sigma_v^2 = 0.35^2 + 0.36^2 = 0.25^{***}$ (and $\lambda = \sigma_u/\sigma_v = 0.97^{***}$) in the NHN, while $\sigma^2 = 0.68^2 + 0.35^2 = 0.59^*$ (and $\lambda = 1.91^{**}$) in the NHN-Z μ .¹⁴

The mean level of technical efficiency $\bar{\theta}$ for the NHN model amounts to 0.772 and spans from 0.317 to 0.943 (Table 7). Additionally controlling for the determinants of inefficiency raises the mean efficiency score to 0.831. Hence, the mean inefficiency of German households in the use of electricity amounts to 0.169, which seems at first glance comparable to Swiss households (Blasch et al. 2017; Boogen 2017), but somewhat higher compared to US households (Alberini and Filippini 2018).

However, the conclusion that efficiency is lower than in the USA would be misleading and a misinterpretation of the SFA estimates as they merely reflect *relative* efficiency rather than absolute efficiency levels. Even households that are labeled as efficient based on the estimation results could still be inefficient in absolute terms. Consequently, a comparison across studies is not possible as the estimated efficient frontier is not the same and dependent on the specific data set. In fact, it seems unlikely that the energy efficiency is lower in Germany than in the USA, as, for instance, the average household electricity consumption in Germany is around 3300 kWh, while it is over 12,000 kWh in the USA (Andor et al. 2020).

Moreover, by including the determinants of inefficiency, the distribution of the efficiency scores becomes wider (Fig. 2), ranging from 0.201 to 0.959 (Table 7).¹⁵ While only 1.5% of the sample households exhibit an efficiency level of less than 50%, around 18% of the sample achieve an efficiency level of at least 90%. Furthermore, mean efficiency increased in the model with determinants from 0.77 to 0.83, as is common in practice when parameterizing the distribution of u_i .

As a robustness check, we estimate a NLS model. The mean efficiency score is 0.767 (see Table 7 and for its distribution Fig. 4 in the Appendix) and the correlation with the efficiency scores from the linear NHN-Z μ model is $\rho=0.61$. The full estimation results for the NLS model can be found in Table 8 in the Appendix. It bears noting that the results are qualitatively the same as those presented in the main text. This indicates that our original specification captures the key features of interest.

We analyze more deeply to what extent the determinants drive efficiency by displaying the efficiency scores for different socioeconomic groups. For starters, Fig. 3a shows that households with four or more members use electricity relatively more efficiently than smaller households. This suggests that larger households can exploit some economies of scale by sharing appliances for instance. Figure 3b illustrates that respondents in West Germany are slightly more efficient than residents of East Germany. The difference amounts to five percentage points and is statistically significant at the 1% level.

Moreover, we find that households with an income of less than EUR 1500 are notably less efficient than wealthy households with an income of at least EUR 4500 (Fig. 3c). This finding can be driven by the fact that wealthier households can afford

¹⁴ Thanks to a reviewer's suggestion, we estimate two alternatives where the determinants enter (i) on the frontier as well as (ii) on the frontier and via the inefficiency term (see Table 9). We find that the log likelihood values for our model in the main text performs somewhat better than (i). Moreover, we find that model (ii) is not well behaved, as γ is close to unity, which we believe to be caused by model misspecification.

¹⁵ Notably, the correlation between the two efficiency scores (with and without determinants of inefficiency) is relatively high ($\rho = 0.841$).

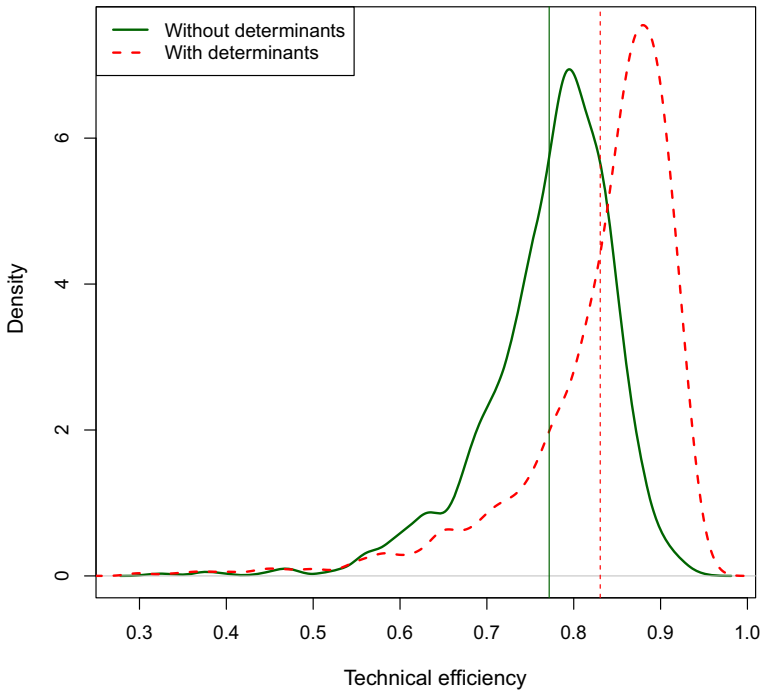
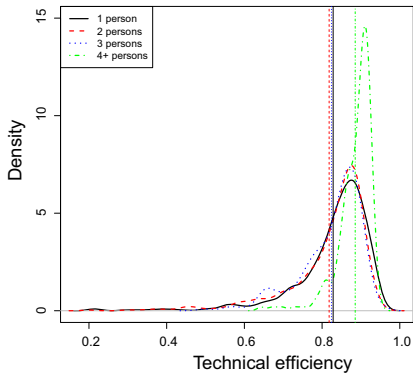


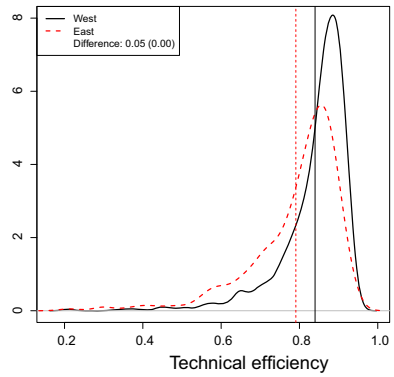
Fig. 2 Distribution of technical efficiency of SFA models

more energy-efficient appliances and have a higher willingness to pay for energy efficiency (Andor et al. 2020; Houde 2018). Furthermore, high-income households exhibit a larger price elasticity (Fronzel et al. 2019), which could result in using electricity more efficiently. In addition, less affluent households might have higher opportunity cost for each Euro of disposable income, as needs, e.g., food, and housing, must first be met before investments in energy efficiency can be made. Not only is the mean of the efficiency score higher among wealthier households, but also their distribution is much narrower. A frequency analysis indicates that three quarters of households with an income below EUR 1500 exhibit lower efficiency scores than the mean of high-income households. Moreover, among the households in the highest decile of the distribution of efficiency, 11% have incomes below EUR 1500, while about a quarter earns incomes larger than EUR 4500.

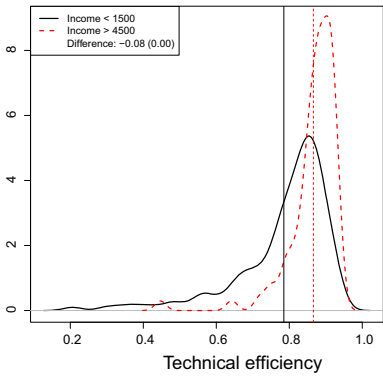
Furthermore, households that reside in their own dwellings tend to use electricity more efficiently than tenants (Fig. 3d). Hence, it might be that homeowners are more attentive to energy issues than tenants. The divergence in efficiency might be rooted in the landlord-dilemma (Allcott and Greenstone 2012): If landlords bear the cost resulting from electricity consumption, tenants are not incentivized to use electricity efficiently. Conversely, if tenants bear the electricity costs, landlords are not incentivized to equip the apartments with an energy-efficient appliance stock. Another reason could be that because of a larger price elasticity (Fronzel et al. 2019), homeowners consume electricity more efficiently. As in the case of income, we observe a



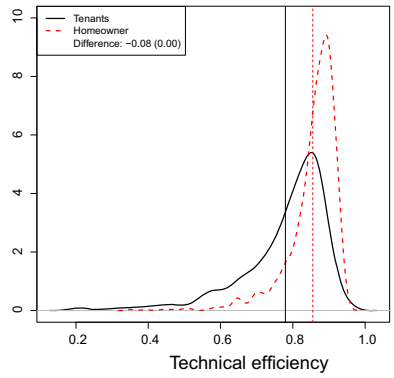
(a) Household size



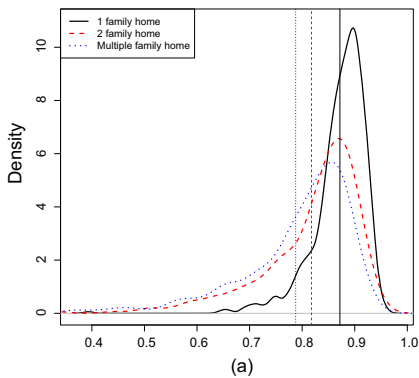
(b) East and West Germany



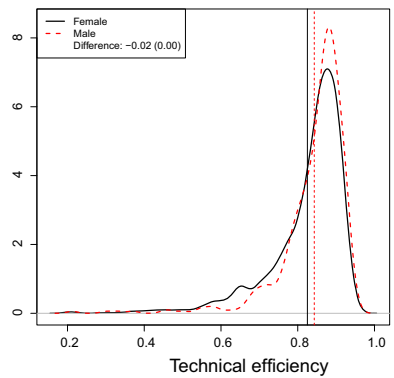
(c) Household income



(d) Homeownership



(e) Building type



(f) Gender

Fig. 3 Heterogeneous technical efficiency

much narrower distribution of energy efficiency among homeowners. While the least efficient 10% of tenants exhibit an efficiency score of 0.50, the least efficient 10% of homeowners show a mean efficiency score of 0.70. However, at the top decile of the distribution, we do not find a considerable difference as the 10% most efficient have an efficiency value of at least 0.95, irrespective of renting or owning the dwelling.

We furthermore find that households that reside in single-family homes use electricity notably more efficiently than households in two or multiple-family homes (Fig. 3e). Lastly, differentiating across gender, we find that households with a male household head tend to use electricity slightly more efficiently (Fig. 3f), even though the difference amounts to merely two percentage points.

6 Conclusion

Growing greenhouse gas emissions have spurred political action inducing individuals to reduce their energy consumption. To optimally develop and align such policies, it is important to study the potentials to save energy in different sectors and determine the best strategies to increase energy efficiency. In general, there are two reasons why households can be inefficient in the use of electricity: consumers might hesitate to invest in energy-efficient technologies (Allcott and Greenstone 2012; Gerarden et al. 2017) or they might use their appliances inefficiently.

In this paper, we applied stochastic frontier analysis (SFA) methods to estimate the efficiency of residential electricity consumption. We used detailed survey data from German households on electricity consumption, the electric appliance stock and its utilization, as well as socioeconomic characteristics. Moreover, we allowed for personal characteristics to influence the level of efficiency, which provides us with insights into how to approach the efficient frontier.

Our results suggest that the mean efficiency level amounts to 83% in the German residential electricity sector. Assuming that this point estimate is exactly true and that the 17% inefficiency could be reduced for the 42 million German households (with an average electricity consumption of 3300 kWh), this results in potential electricity savings of roughly 23.6 billion kWh. Based on the average carbon intensity of the German electricity mix (486 g per kWh, Andor et al. 2020), this would reduce CO₂ emissions by about 11 million tons. Our results therefore indicate considerable energy saving potentials.

Our analysis of determinants of inefficiency revealed that household size, income, homeownership, and the building type are among the main drivers of inefficiency. These results might help to target groups of households that could benefit most from programs, which aim at enhancing energy efficiency, such as energy audits and information campaigns. For instance, we find that low-income households and tenants exhibit lower efficiency values on average than wealthier households and homeowners. Moreover, their distribution of efficiency scores is wider, implying very large conservation potentials at the lower end of the distribution, i.e., among particularly inefficient households. While the existing literature suggests that in particular high consumption households should be targeted (for instance, Allcott 2011 and Andor et al. 2020), our findings indicate additional criteria for targeting.

To foster energy efficiency in Germany, households with less than four members, low-income households, and tenants should be targeted. As demographic trends in Germany indicate that in the future smaller households will be more prevalent, energy policy needs to pay special attention to these households as they exhibit lower efficiency scores. Furthermore, raising households' incomes could increase their energy efficiency level. This could be achieved either by social policy or by energy policy, e.g., via subsidies for energy-efficient appliances and/or transfers for low-income households. Regarding the lower efficiency levels of tenants, policy-makers should aim to mitigate the landlord-tenant dilemma that arises because of diverging incentives. Potential instruments include energy performance contracting and energy labeling (Ástmarsson et al. 2013).

Clearly, all potential measures need a separate evaluation and it is not clear if they should be applied in the end. For instance, Davis et al. (2014) demonstrate that a large-scale appliance replacement program that helped millions of Mexican households replacing their old refrigerators and air conditioners with energy-efficient models was an expensive way to reduce energy use. Similarly, Fowlie et al. (2018) detect negative returns to a US-wide weatherization program.

Furthermore, one needs to bear in mind that energy efficiency improvements might induce a rebound effect that counteracts some of the savings (Orea et al. 2015). Yet, the findings of Chakravarty et al. (2013) and Davis (2008) give hope that the rebound effect is relatively modest for residential electricity consumption because of a low price elasticity and high saturation of electric appliances.

Lastly, we would like to explicitly highlight one methodological aspect to readers who are unfamiliar with efficiency analysis methods as it is important for the interpretation of the results. The estimated mean inefficiency of around 20% seems similar to findings for Switzerland (Blasch et al. 2017; Boogen 2017) but higher than the estimated 10% for the USA (Alberini and Filippini 2018). At first glance, these results might lead to the "naïve" conclusion that the energy efficiency is higher in the USA. However, such a conclusion would be misleading and a misinterpretation of the SFA estimates because they reflect *relative* efficiency and not absolute efficiency levels. If all households in one data set were inefficient in absolute terms, efficiency analysis methods would still determine "efficient" households that define the frontier. Therefore, even the estimated efficient households could still be inefficient in absolute terms.

Consequently, a comparison across studies is not possible because the estimated efficient frontier differs and depends on the specific data set. Given the average household electricity consumption (e.g., around 3300 kWh in Germany vs. 12,000 kWh in the USA), it seems indeed unlikely that the energy efficiency is lower in Germany and Switzerland than in the USA. Future studies could aim to compare the energy efficiency of countries within one study based on disaggregated data. While these considerations furthermore highlight that the application and interpretation of efficiency analysis methods, such as stochastic frontier analysis (SFA) or data envelopment analysis (DEA), might not always be straightforward and thus expert knowledge seems beneficial, we hope that our study, in particular, shows the merits of efficiency analysis methods for political consulting.

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Compliance with ethical standards

Conflict of interest All authors declare that they have no conflict of interest.

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

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Appendix

Table 5 Distribution of socioeconomic characteristics in both our sample and in Germany

	Our sample	Germany (2013)
Household size:		
1-person household	0.304	0.405
2-person household	0.427	0.344
3-person household	0.145	0.125
4+ person household	0.125	0.126
East Germany	0.191	0.211
Income > 4700 EUR	0.107	0.102
Age:		
Age between 18 and 34	0.056	0.192
Age between 35 and 64	0.588	0.526
Age 65 and above	0.356	0.282
Female	0.299	0.352
Children in household	0.170	0.287

Source: Destatis, (2014)

Table 6 SFA estimation results of NHN- $Z\sigma$

	Coeff.	Std. err.
<i>Frontier</i>		
Water heating	0.211***	(0.028)
Air conditioning	-0.123	(0.151)
Electric oven	-0.012	(0.047)
Aquarium/terrarium	0.167***	(0.041)
Waterbed	0.09*1	(0.051)
Sauna	-0.012	(0.038)
Solarium	-0.033	(0.092)
Pond pump	0.110***	(0.028)
Refrigerators	-0.013	(0.011)
Freezers	0.037**	(0.016)
Washing	0.0001	(0.000)
Dish washing	0.0004***	(0.000)
Drying	0.0005***	(0.000)
TV sets	0.033***	(0.011)
PCs	0.014	(0.010)
Light bulbs	-0.002***	(0.001)
Meals	0.0003***	(0.000)
Constant	2.9079	(0.064)
<i>Inefficiency</i>		
Absent	-0.124***	(0.046)
East	0.289	(0.209)
ln(Income)	-0.528**	(0.238)
Homeowner	-0.535*	(0.284)
Two-family home	0.712**	(0.308)
Multiple-family home	1.026***	(0.314)
Age	-0.012	(0.008)
Female	-0.338	(0.207)
Children	-0.451	(0.295)
2 persons household	0.970***	(0.263)
3 persons household	0.963**	(0.374)
4+ persons household	0.405	(0.644)
Constant	1.761	(1.811)
σ_v	0.372***	(0.012)
No. of observations	1,638	

Standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively

Table 7 Distribution of efficiency scores

	NHN	NHN- $Z\mu$	NLS	NHN- $Z\sigma$
Minimum	0.317	0.201	0.400	0.201
25th percentile	0.738	0.803	0.729	0.787
Median	0.786	0.859	0.777	0.842
Mean	0.772	0.831	0.767	0.821
75th percentile	0.823	0.891	0.819	0.881
Maximum	0.943	0.959	0.986	0.994

Table 8 Results of the nonlinear least square model

	Coeff.	Std. err
<i>Frontier</i>		
Water heating	0.228***	(0.028)
Air conditioning	-0.120	(0.156)
Electric oven	0.004	(0.047)
Aquarium/terrarium	0.169***	(0.042)
Waterbed	0.106**	(0.053)
Sauna	-0.004	(0.040)
Solarium	-0.016	(0.097)
Pond pump	0.106***	(0.029)
Refrigerators	-0.008	(0.011)
Freezers	0.036**	(0.017)
Washing	0.000	(0.000)
Dish washing	0.000***	(0.000)
Drying	0.001***	(0.000)
TV sets	0.032***	(0.011)
PCs	0.009	(0.010)
Light bulbs	-0.002***	(0.001)
Meals	0.000***	(0.000)
Constant	2.866***	(0.108)
<i>Inefficiency</i>		
Absent	-0.050**	(0.023)
East Germany	0.174*	(0.093)
ln(Income)	-0.216**	(0.101)
Homeowner	-0.339**	(0.139)
Two-family home	0.144	(0.123)
Multiple-family home	0.286**	(0.142)
Age	-0.004	(0.003)
Woman	-0.196*	(0.102)
Children	-0.144	(0.108)
2 persons household	0.557**	(0.185)
3 persons household	0.656**	(0.235)
4+ persons household	0.453*	(0.254)
Constant	0.503	0.682
No. of observations	1,638	

Standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively

Table 9 SFA estimation results with alternative assumptions on the determinants of inefficiency

	Coeff.	Std. err.	Coeff.	Std. err
<i>Frontier</i>				
Water heating	0.226***	(0.028)	0.219***	(0.028)
Air conditioning	-0.179	(0.158)	-0.144	(0.152)
Electric oven	-0.007	(0.046)	-0.013	(0.045)
Aquarium/terrarium	0.166***	(0.042)	0.162***	(0.040)
Waterbed	0.113**	(0.052)	0.115**	(0.052)
Sauna	-0.008	(0.039)	-0.010	(0.037)
Solarium	0.017	(0.096)	0.034	(0.094)
Pond pump	0.106***	(0.029)	0.108***	(0.028)
Refrigerators	-0.010	(0.011)	-0.014	(0.011)
Freezers	0.039***	(0.016)	0.042***	(0.016)
Washing	0.000	(0.000)	0.000	(0.000)
Dish washing	0.000***	(0.000)	0.000***	(0.000)
Drying	0.001***	(0.000)	0.001***	(0.000)
TV sets	0.027**	(0.010)	0.024**	(0.010)
PCs	0.007	(0.010)	0.005	(0.010)
Light bulbs	-0.002***	(0.001)	-0.002***	(0.001)
Meals	0.000**	(0.000)	0.000**	(0.000)
Absent	-0.005***	(0.002)	-0.010***	(0.003)
East	0.074***	(0.027)	0.100***	(0.029)
ln(Income)	-0.062**	(0.026)	-0.024	(0.026)
Homeowner	-0.083***	(0.029)	-0.072**	(0.030)
Two-family home	0.019	(0.029)	-0.056*	(0.029)
Multiple-family home	0.108***	(0.030)	0.060**	(0.029)
Age	-0.001	(0.001)	0.001	(0.001)
Female	-0.050**	(0.023)	-0.039*	(0.022)
Children	-0.043*	(0.025)	0.005	(0.023)
2 persons household	0.181***	(0.031)	0.175***	(0.033)
3 persons household	0.245***	(0.043)	0.370***	(0.042)
4+ persons household	0.214***	(0.060)	0.256***	(0.059)
Constant	3.313***	(0.216)	3.010***	(0.215)
<i>Inefficiency</i>				
Absent	-	-	1.944	(1.827)
East	-	-	-22.015	(15.252)
ln(Income)	-	-	-26.349	(20.741)
Homeowner	-	-	-4.526	(6.652)
Two-family home	-	-	81.321	(71.382)
Multiple-family home	-	-	59.101	(51.815)
Age	-	-	-1.159	(1.017)
Female	-	-	-7.130	(7.020)
Children	-	-	-148.004	(129.929)
2 persons household	-	-	8.331	(7.578)
3 persons household	-	-	-291.141	(264.310)
4+ persons household	-	-	-18.396	(23.576)
Constant	-	-	72.852	(47.262)
σ^2	0.246***	0.019	34.592	(29.226)
γ	0.518***	0.069	0.997***	(0.003)
No. of observations	1,638			
Log likelihood	-846.88		-811.79	

Standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively

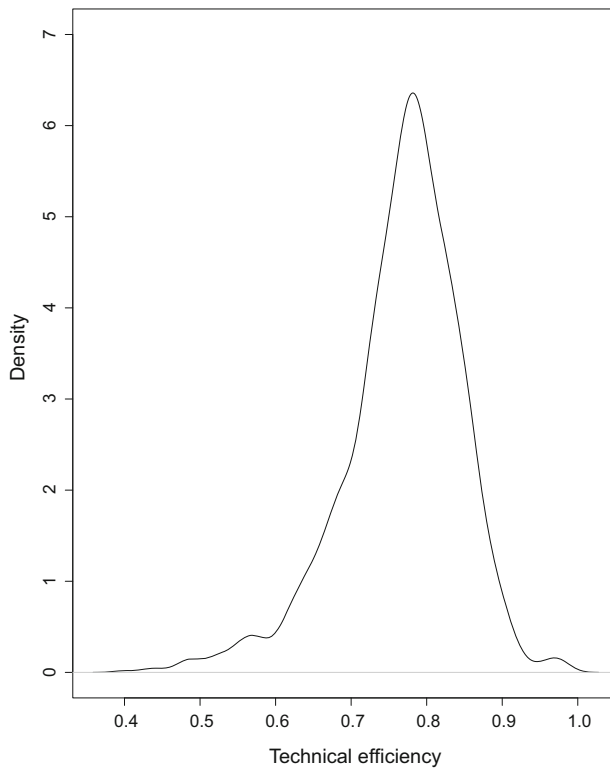


Fig. 4 Distribution of technical efficiency using the NLS model

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