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Heterogeneity in German Residential Electricity Consumption: A quantile regression approach

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ABSTRACT

In the absence of sufficient coverage of metering data on the electricity consumption of individual devices, this paper estimates the contribution of individual appliances to overall household electricity consumption, drawing on the most recent wave of the German Residential Energy Consumption Survey (GRECS). Moving beyond the standard focus of estimating mean effects, we combine the conditional demand approach with quantile regression methods to capture the heterogeneity in electricity consumption rates of individual appliances. Our results indicate substantial differences in these rates, as well as the end-use shares across households originating from the opposite tails of the electricity consumption distribution. This outcome highlights the added value of applying quantile regression methods in estimating consumption rates of electric appliances and indicates some scope for realizing conservation potentials.

1. Introduction

Growing concern about climate change has incited widespread consensus about the need for political action and an intense debate on mitigation measures. In fact, policymakers all around the world have stipulated programs to mitigate climate change. For instance, the European Union (EU) strives for a 40% reduction in greenhouse gas emissions by 2030 relative to 1990, which to a large extent is expected to be achieved by the electricity generation sector. Since households consume a substantial share of electricity, about 30% in the EU (Eurostat, 2018), spurring households to curtail their consumption appears to be a promising approach to reach emission reduction targets.

Although there are a few studies that resort to smart metering technologies that allow measuring the electricity consumption of individual appliances (e.g. Schleich et al., 2013; Chen et al., 2015), little evidence exists on the amount of electricity used by different purposes (for a review of factors that affect electricity consumption, see Jones et al., 2015). To close this void, empirical studies are required that infer a household's total electricity consumption from both the stock of electrical appliances and the electricity consumption rates of individual appliances.

In the absence of sufficient coverage of metering data on the electricity consumption of individual devices, which presumably will not become standard for at least another decade, empirical studies necessarily resort to econometric methods, such as the widely used conditional demand approach (CDA) as suggested, for instance, by Parti and Parti (1980), Aigner et al. (1984), and Lafrance and Perron (1994) and more recently applied by Larsen and Nesbakken (2004) and Dalen and Larsen (2015). This approach draws on dummy variables that indicate the ownership of electric appliances, such as washing machines and dishwashers, and rests on the idea that the corresponding coefficients can be interpreted as the mean electricity consumption related to each type of appliance.

Based on a unique data set originating from the most recent wave of the German Residential Energy Consumption Survey (GRECS) and a subsequent survey on the individual stock of electrical appliances among a subsample of about 2100 households, this paper investigates the heterogeneity in household electricity consumption, which is due to differences in appliance stocks and consumption behavior, by employing quantile regression methods and combining them with CDA. Refining the approach of Larsen and Nesbakken (2004) and Dalen and Larsen (2015) by explicitly including variables that indicate the frequency of appliances and the intensity of use instead of mere appliance ownership, we estimate bandwidths for the electricity consumption rates of individual appliances, thereby accounting for both user behavior and the heterogeneity in electric appliance stocks of households. In addition, we gauge the shares of diverse end-use purposes for households located in different parts of the electricity consumption

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distribution.

In contrast to previous studies that employ quantile regression methods, our analysis is based on consumption rather than expenditure data (e.g. Huang, 2015) and on the appliance stock, rather than household attributes alone (e.g. Kaza, 2010; Valenzuela et al., 2014; Yao et al., 2014). While an advantage of the CDA is that electricity consumption rates of appliances and end-use shares are directly estimated (Larsen and Nesbakken, 2004), some CDA studies find implausible or even negative consumption rates of electric appliances (e.g. Caves et al., 1987).

Our analysis demonstrates large heterogeneity in residential electricity consumption, which is even evident for households of the same size. It may not only reflect differences in appliance stocks and intensities of use, but also significant discrepancies in both the electricity consumption rates of the appliances and heterogeneous consumer behavior. It turns out that employing quantile regression methods allows for eliciting the spectrum of consumption rates for each type of appliance, which covers the whole range from less energy-efficient to highly efficient appliances. In addition, while these results clearly reflect correlations, rather than causal relationships, we find substantial differences in the end-use shares across households originating from the opposite tails of the electricity consumption distribution, highlighting the added value of applying quantile regression methods in estimating consumption rates of electric appliances.

Furthermore, our results indicate energy saving that can be realized by focusing conservation policies on particular appliances, such as refrigerators. For example, encouraging the purchase of energy-efficient models through subsidies can help to reduce both electricity consumption and related greenhouse gas emissions. Another large saving potential is found for lighting, which is caused by both less efficient light bulbs and inefficient utilization. This calls for a more intensive information policy on energy efficiency that aims at both revealing conservation potentials and on behavioral changes. The latter is important given the existence of the so-called rebound effect that undermines the realization of savings, at least to some degree (Sorrell et al., 2009).

The following section describes the data set underlying our analysis. Section 3 presents the methodology, followed by a presentation of the estimation results in Section 4 and of end-use shares in Section 5. The last section summarizes and concludes with policy recommendations.

2. Data

To estimate the consumption rates of households' electrical appliances, we draw on data obtained from two surveys that were conducted jointly by RWI – Leibniz Institute for Economic Research and the professional German survey institute *forsa*. As part of the German Residential Energy Survey (GRECS) that was established in 2005 (RWI and forsa, 2005), the first survey took place at the outset of 2014 and gathered data on the electricity consumption of 8500 private households, as well as socio-economic household characteristics (RWI and forsa, 2015). Among other issues, survey respondents – in our case the household heads, who, by definition, are responsible for the financial decisions at the household level – were requested to provide detailed information on their electricity bills for the years 2011–2013, including electricity prices per kilowatthour (kWh), monthly fixed fees, and electricity consumption in the respective billing periods.

Using the starting and ending date of each bill and the household's individual electricity consumption in kWh, we calculate the household's mean consumption per day and infer its annual electricity consumption by multiplying the daily average by 365 days. In this respect, the GRECS contrasts with many surveys in which respondents provide the monetary amount spent on electricity, rather than consumption data in kWh. For instance, in the US Consumer Expenditure Survey, consumption levels are instead imputed using expenditure data and the average price in the respondents' area (Fell et al., 2014), which results in less precise information on individual consumption than that provided by the GRECS.

While it is difficult to distinguish outliers and misinformation from true consumption values, we only use electricity bills with a duration of more than 180 days to exclude seasonal impacts and generously sacrifice household observations that exhibit suspicious per-capita consumption and price figures. To this end, we employ an iterative procedure that in each iteration drops all observations that deviate from the mean per-capita consumption level and the mean price by more than the twofold of the standard deviation.

Mean per-capita consumption and price levels, as well the respective standard deviations, are recalculated in each iteration, with the procedure coming to an end when no further observations are dropped.[1] From the large pool of several thousand households with plausible information on their electricity consumption that is validated in this way, subsequently about 2100 households were randomly selected to be interviewed in a second survey that followed in mid-2014. Its main purpose was to gather information on the households' appliance stock and its utilization.

A salient result originating from these surveys is the heterogeneity of residential electricity consumption (Fig. 1). The fact that the kernel densities are not symmetric but skewed to the right indicates that there are a few households with consumption levels that are substantially higher than the average consumption of households of the same size. Moreover, the heterogeneity obviously increases with the number of household members. In fact, 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. The larger heterogeneity among larger households is likely to be caused by a larger appliance stock. As household size heavily matters for electricity consumption, it bears noting that with shares of about 31% and 42%, respectively, single- and two-person households represent the overwhelming majority of our sample, whereas households with three and more members are relatively rare (Table 1).

Compared to the German population, single-person households are slightly less present in our sample, while two-person households are somewhat over-represented (Table A1 in the appendix). Moreover, elderly respondents are somewhat overrepresented in our sample. We have explored whether these discrepancies bear on the regression results by incorporating household weights. As the differences in the estimates between the weighted and unweighted regression are negligible, in what follows, we focus on the unweighted results.

With respect to user behavior, our analysis takes into account that households were absent from home for, on average, three and a half weeks over the year (Table 2). In addition, we gathered information on the ownership of major appliances and their utilization. Among the behavioral covariates that affect consumption is the number of washing cycles in the four weeks prior to the survey. This information is extrapolated to the period of one year to gauge the annual electricity consumption for washing purposes. On average, washing machines, as well as dishwashers, are used almost every second day, conditional on owning these appliances. With a penetration rate that slightly exceeds 50%, tumble dryers are considerably less prevalent among German households than washing machines and dishwashers. Moreover, with about 100 utilizations, tumble dryers are used less frequently than washing machines and dishwashers.

Gathering data on the utilization of some appliances may be prone to large uncertainties. For instance, it is unlikely that the household head of a multi-person-household is able to provide reliable

[1] In the first survey, which aimed at eliciting the electricity consumption, 5220 of the 8561 participating households disclosed billing information, from which we dropped 274 households with night storage heating systems, as their electricity consumption is substantially above average. Further 321 households were removed from the sample after the cleaning procedure.

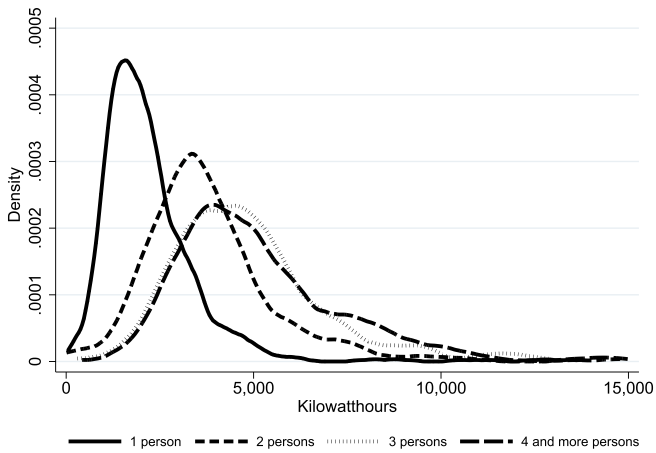

Fig. 1. Distribution of Electricity Consumption for various Household Sizes.

Table 1
Summary statistics of socioeconomic characteristics.

Variables	Mean or Share	Std. Dev.	Number of observations
1-Person household	0.308	–	2105
2-Person household	0.422	–	2105
3-Person household	0.140	–	2105
Household with 4 or more members	0.130	–	2105
Age (in years)	58.0	12.8	2106
East Germany	0.193	–	2106
Household net income (in €)	2800	1293	1968
Full-time employed	0.435	–	2077
Part-time employed	0.133	–	2077
Not employed	0.432	–	2077
Property owner	0.674	–	2106
Single-family house	0.442	–	2101
Duplex house	0.172	–	2101
Apartment building	0.386	–	2101
Female	0.309	–	2106
Living area (in square meters)	113.6	48.9	2103
High-school degree	0.380	–	2100
# Children in household	0.282	0.688	2085
Electricity price (in Cents per kWh)	22.7	6.4	1743
Electricity consumption (in kWh per year)	3646	2089	2106

information on the time spent watching television or using the computer by all household members. Therefore, in our estimations, we draw on the number of such appliances that are present in a household, as this information can be assumed to be collected with a substantially higher precision than that on usage behavior. On average, German households possess 1.73 TV sets and virtually each German household has a laptop and a personal computer.

Other household appliances, such as refrigerators and freezers, whose mean numbers per household amount to 1.35 and 0.72, respectively, run the whole day and permanently need electricity. Thus, particularly in this case, it should suffice to count the number of appliances available in a household. In contrast, for less common appliances, such as aquaria and terraria, air conditioners, saunas, waterbeds, and solaria, we only gather whether the households hold them.

The appliances displayed in Table 2 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 devices with modest consumption rates, such as electric tooth brushes, water kettles, bread cutters, hoovers, chargers, etc. Instead of explicitly accounting for these and other small appliances in our estimations, the associated electricity consumption is captured by the constant term and household size dummies. As the number of small appliances tends to increase with the number of household members, it is plausible to assume growing coefficients for the household size dummies.

Table 2
Summary Statistics of Electric Appliances and their Usage.

Variables	Type	Mean or Share	Std. Dev.	Number of Observations
# Weeks absent from home	Count	3.53	4.52	1996
Water heating	Dummy	0.176	–	2093
Dishwasher	Dummy	0.824	–	2079
# Washing cycles per year	Count	185.8	112.3	1674
Washing machine	Dummy	0.958	–	2098
# Washing cycles per year	Count	184.5	147.4	1991
Tumble Dryer	Dummy	0.556	–	2098
# Drying cycles per year	Count	98.2	98.1	1130
Electric oven	Dummy	0.941	–	2079
# Meals	Count	317.8	136.8	2100
# Refrigerators	Count	1.35	0.58	2050
# Freezers	Count	0.72	0.64	2085
# TV sets	Count	1.73	0.89	2054
# Personal computers	Count	0.94	0.82	2099
# Laptops	Count	1.00	0.91	2099
# Light bulbs	Count	25.11	15.92	1971
Aquarium or Terrarium	Dummy	0.062	–	2094
Waterbed	Dummy	0.041	–	2094
Sauna	Dummy	0.075	–	2094
Pond pump	Dummy	0.160	–	2094
Air-conditioning	Dummy	0.004	–	2106
Swimming pool	Dummy	0.001	–	2094
Solarium	Dummy	0.012	–	2094

3. Methodology

The conditional demand approach (CDA) employs data on appliance stocks to quantify the effect of an appliance type on the electricity consumption level, conditional on possessing this appliance. In CDA studies (e.g. Hsiao et al., 1995; Halvorsen and Larsen, 2001; Larsen and Nesbakken, 2004; Reiss and White, 2005; Dalen and Larsen, 2015), dummy variables D_{ij} play a key role in explaining the electricity consumption y_i of household i, where D_{ij} equals unity if household i possesses appliance j and zero otherwise.

Our point of departure in estimating the determinants of electricity consumption largely follows Dalen and Larsen (2015), with the modification that, in addition to dummy variables that control for the existence of an appliance type in a household, such as a solarium and an air-conditioner, we include count variables N_{ik} for those appliance types k that may emerge in a higher frequency than unity in a household, such as TV sets and notebooks, as well as for those appliance types for which information on usage intensity is available, such as the number of washing cycles of dishwashers:

$$\begin{aligned} y_i = \alpha_1 &+ \sum\nolimits_{l=2}^{L} \alpha_l S_{il} + \sum\nolimits_{j=1}^{J} \beta_j D_{ij} + \sum\nolimits_{k=1}^{K} \theta_k N_{ik} \\ &+ \sum\nolimits_{j=1}^{J} \sum\nolimits_{m=1}^{M} \rho_{jm} (C_{im} - \bar{C}_{jm}) D_{ij} \\ &+ \sum\nolimits_{k=1}^{K} \sum\nolimits_{m=1}^{M} \rho_{km} (C_{im} - \bar{C}_{km}) N_{ik} + \varepsilon_i, \end{aligned} \tag{1}$$

where α_1 reflects a single-person household's base consumption, which is estimated along with the other parameters α_l, β_j, θ_k, ρ_{jm}, and ρ_{km}, and ε_i denotes a stochastic error term. S_{il} denote dummy variables that capture household size in terms of the number of household members: S_{il} equals unity if household i has $l = 2, \ldots, L$ household members, where L denotes household types with four and more members. Household size dummies S_{il} are included to capture the residual electricity consumption that is due to all those appliances that are not explicitly included in the specification by dummy or count variables.

Furthermore, the interaction terms $\sum_{m=1}^{M} \rho_{jm}(C_{im} - \bar{C}_{jm})D_{ij}$ and $\sum_{m=1}^{M} \rho_{km}(C_{im} - \bar{C}_{km})N_{ik}$ reflect deviations from the mean values of household and dwelling characteristics, such as dwelling size, electricity prices and household income. These characteristics are taken into account in the form of the variables C_{im} $(m = 1,2, \ldots, M)$, with $\bar{C}_{jm}: =1/H_j \sum_{i=1}^{n} C_{jm}D_{ij}$ designating the mean value of these household characteristics for the H_j households that possess appliance j and n denoting the number of sample households. Analogously, $\bar{C}_{km}: =1/H_k \sum_{i=1}^{n} C_{km}N_{ik}$ is the mean value of the household characteristics of the H_k households that possess at least one appliance of type k or use it at least once. Parameter β^j reflects the mean electricity consumption of appliance j given that for all M household characteristics the variables C_{im} are equal to the respective variable means calculated over all households that hold appliance j: for all $m = 1,2,\ldots,M$.

Note that in Specification (1), appliances are either captured by a dummy variable D_{ij} or by a count variable N_{ik}, but not by both. For instance, washing and dish washing is accounted for by the number of annual washing cycles to reflect usage intensity, but not by the availability of washing machines and dishwashers in the form of a dummy variable. Accordingly, in case of washing appliances, parameter θ_k describes the mean electricity consumption of an additional washing cycle. Similarly, for appliance types that may emerge in a higher frequency than unity in a household, such as TV sets and computers, θ_k provides the mean electricity consumption of an additional appliance.

Commonly, Equation (1) is estimated using Ordinary (OLS) or Generalized Least Squares (GLS) methods (e.g. Larsen and Nesbakken, 2004; Dalen and Larsen, 2015), which focus on estimating the conditional expectation function (CEF), $E(y_i|\mathbf{x}_i)$, thereby yielding a uniform effect of each explanatory variable (Frondel et al., 2012). To provide a comprehensive picture of the relationship between electricity consumption y and its determinants at different points in the conditional distribution of y, we additionally employ quantile regression methods, which have been previously employed in a similar vein by, for instance, Kaza (2010), Schleich et al. (2013), Valenzuela et al. (2014) and Huang (2015).

Using quantile regression methods allows for more flexibility in the estimation of the appliances' effect on residential electricity consumption by enabling us to estimate a range of conditional quantile functions (CQF) $Q_\tau(y_i|\mathbf{x}_i)$:

$$Q_\tau(y_i|\mathbf{x}_i) = \alpha(\tau) + \mathbf{x}_i^T \alpha_{\mathbf{x}}(\tau) + F_{\varepsilon_i}^{-1}(\tau), \tag{2}$$

where τ specifies the quantile in the distribution of electricity consumption and may take on values between zero and unity. $\mathbf{x}$ denotes the vector of explanatory variables and $\alpha_{\mathbf{x}}(\tau)$ indicates the varying effect of holding or using a certain appliance on the households' consumption depending upon its consumption level. $F_{\varepsilon_i}^{-1}(\tau)$ denotes the inverse of the cumulative distribution function of ε_i. The most attractive feature of the quantile regression method is that it generally provides for a richer characterization of the data than OLS. Moreover, quantile regressions are more robust to outliers than OLS regression methods. In fact, OLS regressions can be inefficient when the dependent variable has a highly non-normal distribution (Koenker, 2005).

For an arbitrary $\tau \in (0,1)$, the parameter estimates are obtained by solving the following weighted minimization problem:

$$\min_{\alpha(\tau),\alpha_{\mathbf{x}}(\tau)} \sum_{r_i>0} \tau r_i + \sum_{r_i<0} (1-\tau)|r_i|, \tag{3}$$

where underpredictions $r_i: =Q_\tau(y_i|\mathbf{x}_i) - \hat{Q}_\tau(y_i|\mathbf{x}_i) > 0$ are penalized by τ and overpredictions $r_i < 0$ by $1 - \tau$. This is reasonable, as for large τ one would not expect low estimates $\hat{Q}_\tau$ and vice versa, so that these incidences have to be penalized accordingly. Just as OLS fits a linear function to the dependent variable by minimizing the expected squared error, quantile regression fits a linear model using the generally asymmetric loss function

$$\rho_\tau(r): =\tau 1(r > 0)r + (1-\tau)1(r \le 0)|r|, \tag{4}$$

where $r: =Q_\tau - \hat{Q}_\tau$ and the indicator function $1(r > 0)$ indicates positive residuals r and $1(r \le 0)$ non-positive residuals, respectively. Loss function $\rho_\tau(r)$ is also called a "check function", as its graph looks like a check-mark. Minimization Problem (3) can be solved by linear programming techniques (Koenker, 2005) and the variances can be estimated using a method suggested by Koenker and Bassett (1982), but bootstrap methods are often preferred and are used here.

Subsequent to estimating the individual electricity consumption rate of appliances by regression analysis, we calculate the shares of electricity consumption that can be attributed to diverse end-use purposes, such as cooling and lighting. To this end, building upon Dalen and Larsen (2015), we employ the mean values $\bar{D}_j(\tau): =\frac{1}{n}\sum_{i=1}^{n} D_{ij}(\tau)$ for the frequency of appliance type j in quantile τ and multiply it with the corresponding estimate $\hat{\beta}_j(\tau)$ of the consumption rate for quantile τ to predict the electricity consumption of appliance j for "average" households for which, by definition, the interaction terms $\sum_{m=1}^{M} \rho_{jm}(C_{im} - \bar{C}_{jm})D_{ij}$ in Equation (1) vanish. The predicted consumption of appliance j therefore reads: $\hat{y}_j(\tau) = \hat{\beta}_j(\tau)\bar{D}_j(\tau)$.

The predicted share of appliance j for quantile τ is then given by $\hat{s}_j(\tau): =\frac{\hat{y}_j(\tau)}{y(\tau)}$, where $y(\tau)$ denotes total electricity consumption of all households of quantile τ. In a similar vein, for appliances for which their number N_{ik} is employed as a regressor, the predicted share is given by $\hat{s}_k(\tau): =\frac{\hat{y}_k(\tau)}{y(\tau)}$, where $\hat{y}_k(\tau) = \hat{\theta}_k(\tau)\bar{N}_k(\tau)$ and $\hat{\theta}_k(\tau)$ denotes the corresponding electricity consumption rate estimate and $\bar{N}_k(\tau) = \frac{1}{n}\sum_{i=1}^{n} N_{ik}(\tau)$ designates the mean number of appliance type k or the number of applications in quantile τ. Finally, to determine the shares of diverse end-uses in total household consumption, we add up the individual shares of those appliances that contribute to a certain end-use purpose. In the end, we distinguish between the following end-use categories: warm water, lighting, cooling, information and communication technology (ICT), cooking, washing, dish-washing, drying and a remainder to which we refer to as miscellaneous purposes.

4. Results

As a starting point of our analysis, we analyze the conditional demand model by estimating Equation (1) via OLS. We find that few coefficients ρ_{jm} and ρ_{km} of the interaction terms between the appliance dummies D_{ij} or the count variables N_{ik} with the household characteristics C_{im} are statistically different from zero. Furthermore, for most coefficients, the inclusion of these interaction terms has only a negligible bearing on the other coefficient estimates (see Table A2 in the appendix). More disconcerting, however, is that some coefficient estimates are negative, which is not uncommon for this approach (Aigner et al., 1984; Caves et al., 1987; Hsiao et al., 1995; Matsumoto, 2016). For expositional purposes, we consequently present only the results of the OLS and quantile regressions without interaction effects, i.e. without controlling for socio-economic and housing characteristics.

The OLS regression results presented in the first column of Table 3 indicate that less common appliances among German households exhibit the highest electricity consumption rates. For instance, the estimated mean electricity consumption of waterbeds amounts to more than 500 kWh per annum, and that of aquaria and terraria is even higher, at about 760 kWh. The average electricity consumption of more common appliances is much lower, at about 300 kWh per annum for refrigerators, about 400 kWh for freezers, 114 kWh for TV sets, and about 70 kWh for computers.

Table 3
OLS and Median Regression Results for annual Residential Electricity Consumption (in kWh).

	OLS Regression		Median Regression	
	Coeff.s	Std. Err.s	Coeff.s	Std. Err.s
Household Size				
2 Members	836.84**	(83.68)	743.44**	(84.35)
3 Members	1351.42**	(130.02)	1257.19**	(156.16)
4 and more members	1312.72**	(159.46)	1174.58**	(164.06)
Per week absent from home	−22.22**	(7.91)	−16.06	(10.83)
Water heating	464.84**	(88.70)	476.18**	(76.47)
Air-conditioning	525.87	(473.53)	451.19	(397.52)
Per refrigerator	297.19**	(66.23)	394.53**	(69.21)
Per freezer	407.04**	(61.18)	447.13**	(56.46)
Electric oven	92.94	(112.69)	49.26	(108.09)
Per washing cycle	0.69	(0.36)	0.46	(0.35)
Per dish washing cycle	1.31**	(0.36)	1.50**	(0.37)
Per drying cycle	2.71**	(0.53)	2.73**	(0.54)
Per TV set	113.81**	(42.02)	129.61**	(43.48)
Aquarium or terrarium	757.60**	(157.36)	782.93**	(208.94)
Waterbed	519.23*	(224.76)	298.15	(263.64)
Sauna	290.88*	(146.15)	245.30	(160.81)
Solarium	416.48	(518.70)	376.60	(579.81)
Pond pump	374.43**	(102.94)	363.70**	(103.41)
Per computer	69.26*	(35.23)	117.66**	(34.76)
Per light bulb	10.30**	(2.67)	4.40	(2.74)
Per meal	0.41	(0.27)	0.22	(0.29)
Constant	658.48**	(159.95)	512.89**	(167.50)
Number of observations	1653		1653	
(Pseudo-)R^2	0.4726		0.3196	

Note: * denotes significance at the 5% level, ** at the 1% level. In the case of the OLS regression, robust standard errors are reported, while for the median regression, we report bootstrapped standard errors.

While the survey focused on major household appliances, many appliances could not have been included in our regressions due to the lack of data. One reason for this lack is that the data collection for appliances with low consumption rates, such as electric tooth-brushes, coffee machines, microwaves, hoovers, etc., would have increased the respondents' time requirements. The residual consumption resulting from the exclusion of such appliances is reflected by both the constant term and the coefficients for the household size dummies. As expected (see Fig. 1), it turns out that electricity consumption is higher among households with more members. For instance, the OLS estimate of the residual consumption for two-person households is almost 840 kWh higher than that for single-person households (Table 3). Three-person households and households with four and more members exhibit an even higher residual consumption. These residual consumption values generally differ, because the number, size, as well as the intensity of use, of the excluded appliances tend to increase with household size.

As we cannot control for the size, type, wattage, and utilization of all appliances, the OLS coefficient estimates refer to an appliance of average size, efficiency and utilization. In the absence of such data, differences in these characteristics may be captured by employing a quantile regression model, as given by Equation (2). With this approach, we generally find that the estimates of the consumption rates of appliances are smaller for households from the lower tail of the electricity consumption distribution than those of appliances of households from the upper tail (Table 4). Possibly, this reflects that households at the upper tail of the distribution, i.e. households with a large electricity consumption, exhibit a higher intensity of use or hold appliances with lower efficiency levels.

For example, according to our quantile regression results, for refrigerators of households from the 25th percentile, i.e. households with a low electricity consumption, the consumption rate estimate amounts to 250 kWh, which is close to the reference value of 270 kWh reported by the German Council for the Efficient Use of Energy (HEA, 2011) for new, energy-efficient refrigerators. In turn, the estimated consumption rate for refrigerators of households at the 75th percentile amounts to 318 kWh and, thus, is about 25% higher compared to households at the first quartile. Hence, if high-consumption households had the same refrigerator that is used by low-consumption households, their annual savings would amount to about 65 kWh, which is equivalent to 1.7% of their electricity consumption. Given the current electricity price of 30 cents per kWh, these households could save about €20 per year a small amount of money and energy savings that does not provide for substantial incentives to invest in more efficient refrigerators. Similarly, by adopting the low-consumption dishwasher and maintaining the average number of 186 cycles (Table 2), high-consumption households could save 95 kWh (€28) per year.

While we find large differences in the point estimates for most appliances, with a few exceptions, the null hypothesis H_0: $\alpha(\tau_{25}) = \alpha(\tau_{75})$ of equal coefficients for the 25th and the 75th percentile cannot be rejected – see the F statistics in the last column of Table 4. Yet, we find substantial differences across the household size indicators. In fact, the F statistics indicate statistically significant differences for all two- and three-person households. Stark discrepancies in electricity consumption rates can also be observed for energy-intensive appliances, such as waterbeds and light bulbs. For instance, for households belonging to the 25th percentile of the electricity consumption distribution, an additional light bulb increases consumption by merely about 5 kWh, whereas for households at the 75th percentile the effect of an additional bulb is around 16 kWh.

The heterogeneity in the electricity consumption rates of light bulbs becomes even more apparent from Fig. 2: While consumption rates are quite homogenous for percentiles below the median, heterogeneity arises for higher percentiles, with the estimate for the 90% percentile being statistically different from the OLS estimate. In addition to Fig. 2, the appealing character of quantile regression methods is also revealed by Fig. 3, as it shows that households at the 25th percentile typically possess freezers that exhibit a low consumption rate of about 380 kWh per annum (Table 4), whereas freezers of households at the 75th percentile consume 87 kWh more electricity. Multiplied with the average electricity price of 30 cents per kWh, annual savings of €26 can be realized when adopting low-consumption freezers.

5. End-use shares

Using the quantile regression estimates reported in Table 4 and the formulae $\hat{s}_j(\tau) := \frac{\hat{y}_j(\tau)}{y(\tau)}$ and $\hat{s}_k(\tau) = \frac{\hat{y}_k(\tau)}{y(\tau)}$ explained at the end of the methodology section, we now present the shares of electricity consumption that can be attributed to diverse end-use purposes for households belonging to different parts of the consumption distribution (Figs. 4–6). Note that heating purposes do not appear in these figures, as households heating solely with electricity were not invited to participate in our second survey, given the fact that, in contrast to other countries, such as France and Norway, heating solely with electricity is not common in Germany. In fact, according to RWI and forsa (2015), the share of these households is about 3%.

Similarly, heating water with electricity is not very common in German households either: only $\bar{D}_j = 17.6\%$ of the responding sample households use electricity for this purpose (Table 2). As a consequence, the share of water heating in the total electricity consumption of those households that are located in the middle of the consumption distribution is as low as 3.4% (Fig. 4). By contrast, with a share of 27.2%, cooling purposes play a substantial role in Germany's residential electricity consumption. This share includes the electricity demand of refrigerators and other cooling devices. To a lesser extent, it also includes air-conditioners, although this appliance is barely used in German households:

Table 4
Quantile Regression Results for annual Residential Electricity Consumption (in kWh).

	Percentiles						F-Statistics for
	25th		50th		75th		
	Coeff.s	Std. Err.	Coeff.s	Std. Err.	Coeff.s	Std. Err.	$\alpha(\tau_{25}) = \alpha(\tau_{75})$
Household Size							
2 Members	566.42**	(96.92)	743.44**	(83.40)	916.46**	(103.75)	8.02**
3 Members	986.92**	(153.32)	1257.19**	(152.77)	1611.52**	(221.57)	7.67**
4 and more members	975.96**	(146.92)	1174.58**	(167.94)	1241.11**	(224.89)	1.27
Per week absent from home	−20.30*	(9.96)	−16.06	(10.18)	−27.18**	(8.03)	0.47
Water heating	372.76**	(68.45)	476.18**	(82.46)	495.79**	(117.40)	1.17
Air-conditioning	540.24	(815.75)	451.19	(528.53)	513.62	(792.55)	0.00
Per refrigerator	253.02**	(66.96)	394.53**	(65.34)	318.34**	(97.32)	0.45
Per freezer	376.08**	(52.07)	447.13**	(54.52)	463.24**	(89.32)	0.99
Electric oven	62.82	(102.62)	49.26	(110.93)	93.31	(187.69)	0.03
Per washing cycle	0.85*	(0.37)	0.46	(0.37)	0.55	(0.54)	0.34
Per dish washing cycle	1.15**	(0.35)	1.50**	(0.38)	1.66**	(0.47)	0.97
Per drying cycle	2.73**	(0.56)	2.73**	(0.56)	3.11**	(0.78)	0.20
Per TV set	96.12*	(41.55)	129.61**	(44.50)	118.81*	(49.73)	0.20
Aquarium or terrarium	656.21**	(132.41)	782.93**	(212.12)	845.90**	(325.67)	0.36
Waterbed	296.47	(166.79)	298.15	(265.35)	1040.30**	(347.40)	5.05*
Sauna	393.69**	(136.80)	245.30	(151.97)	337.74	(226.30)	0.06
Solarium	44.25	(514.48)	376.60	(526.49)	629.35	(1006.10)	0.32
Pond pump	375.49**	(111.79)	363.70**	(96.93)	385.44**	(144.19)	0.00
Per computer	57.84	(38.19)	117.66**	(34.21)	81.29	(47.14)	0.19
Per light bulb	5.28*	(2.32)	4.40	(2.99)	15.94**	(3.75)	8.34**
Per meal	0.36	(0.24)	0.22	(0.28)	0.29	(0.34)	0.03
Constant	376.71*	(168.10)	512.89**	(173.56)	980.79**	(228.67)	6.78**
Number of observations	1653		1653		1653		
Pseudo-R^2	0.3188		0.3196		0.3123		

Note: * denotes significance at the 5% level, ** at the 1% level. Bootstrapped standard errors are reported.

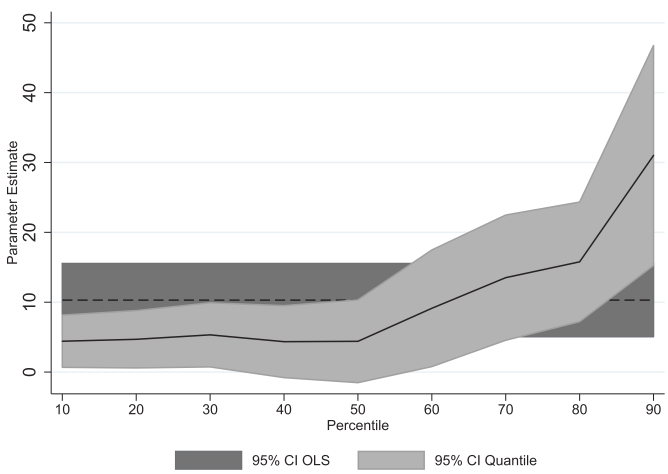

Fig. 2. Comparison of OLS and quantile regression results for the electricity consumption rates of light bulbs.

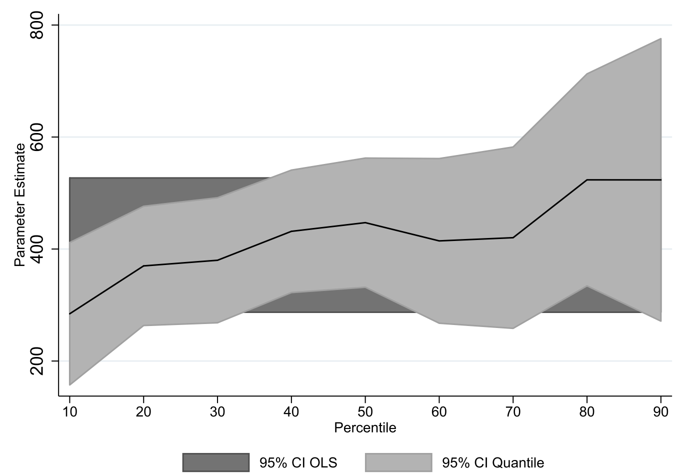

Fig. 3. Comparison of OLS and quantile regression results for the electricity consumption rates of freezers.

only 0.4% of our sample households employ air-conditioning devices (Table 2). Another – increasingly important – end-use is information and communication technology (ICT), which encompasses here the consumption of personal computers, laptops, and television sets. The respective share amounts to 13.0% for the median consumer.

With 35.6%, miscellaneous purposes by far account for the largest share in electricity consumption of the median consumer. This is partly due to the fact that this share includes all appliances that are not explicitly attributed to the categories displayed in Fig. 4. In fact, the miscellaneous share is based on the estimates of the constant, the household size dummies as well as less common appliances, such as waterbeds, saunas, pond pumps, swimming pools, etc.

As becomes evident from our quantile regression results, as well as from Figs. 5 and 6, the importance of end-use purposes varies across the percentiles of the residential electricity consumption distribution. For instance, for households belonging to the 75th percentile of the distribution (Fig. 6), cooling and cooking purposes are of a notably smaller significance than in households of the 25th percentile (Fig. 5), while the miscellaneous share of 44.5% is somewhat higher than the respective share for median consumers. Likewise, with a share of 9.8%, lighting purposes appear to be more relevant in households with a high electricity consumption than in median households and households with a very low consumption. All these differences highlight the added value of applying quantile regression methods in estimating the end-use shares of various consumption categories.

6. Conclusion and policy implications

Employing the conditional demand approach and combining it with quantile regression methods, this paper has estimated the contribution

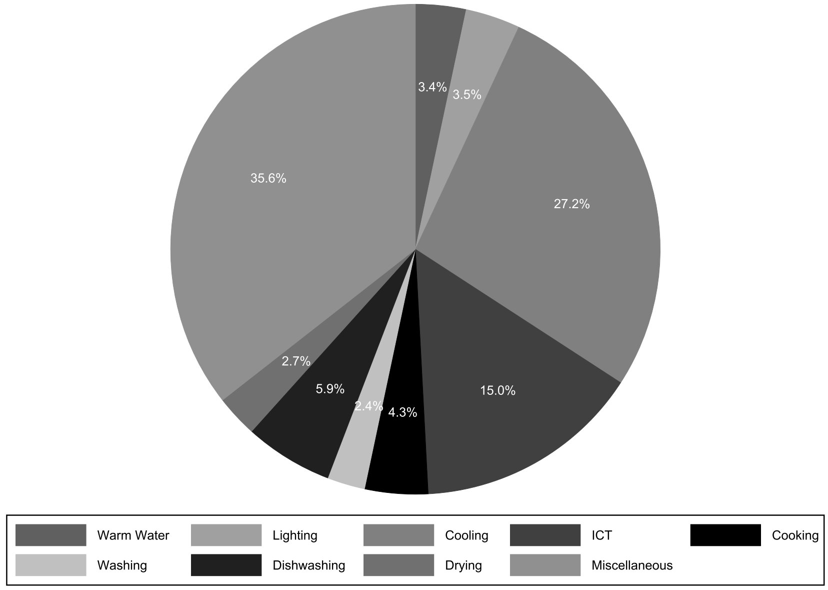

Fig. 4. Shares of various End-Use Purposes for the 50th Percentile in German Residential Electricity Consumption.

of common household appliances to electricity demand from a sample of about 2100 German households. Moving beyond the standard focus of estimating mean effects via OLS, we have applied quantile regression methods to capture the heterogeneity in the electricity consumption rates of individual appliances across quantiles of the electricity consumption distribution. This approach presents a viable alternative to measuring the contribution of each individual appliance to household electricity demand via metering.

Additionally aggregating the consumption rates of distinct appliances into broader end-use categories, we find substantial differences in the end-use shares across households originating from the opposite tails of the electricity consumption distribution, highlighting the added value of applying quantile regression methods in estimating consumption rates of electric appliances. Our analysis reveals that households with relatively low consumption figures tend to consume electricity for more basic services, such as cooling and water heating. Our findings also suggest that there is a stark variation in appliance holdings, as households belonging to the upper tail of the electricity distribution tend to use more electricity per appliance usage than those belonging to the lower tail. This may suggest that upper-tail households own more, larger, older, and more inefficient appliances compared to their counterparts at the lower tail.

With respect to policy recommendations, we deem carbon pricing to be the most effective measure to reduce electricity consumption, as it directly confronts consumers with the costs of appliance use, particularly high-consumption households, and thereby influences their behavior on both the extensive margin of technology choice and the intensive margin of usage. The European Emissions Trading system, for example, provides a mechanism for transmitting carbon price signals. In fact, the recent rise in allowance prices will translate into higher electricity prices presuming that electricity suppliers pass on the higher input costs of generation to consumers.

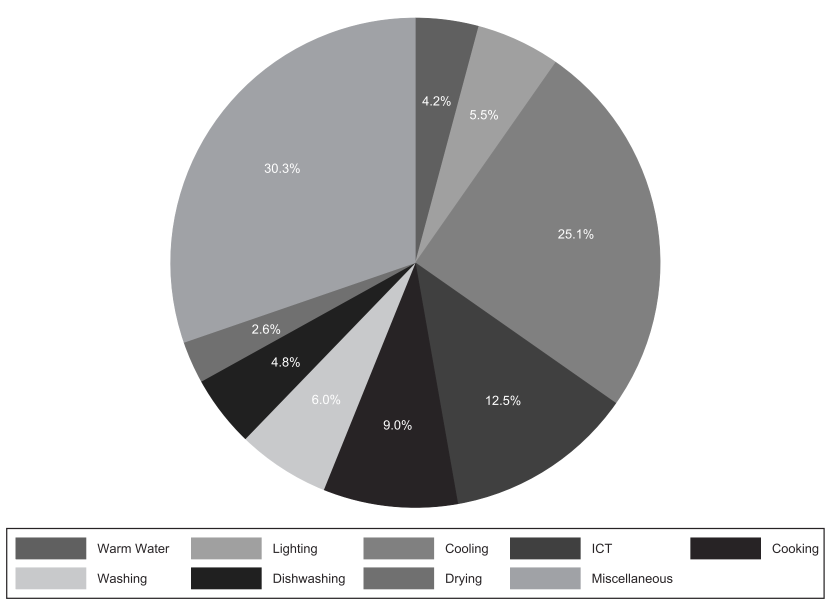

Fig. 5. Shares of various End-Use Purposes for the 25th Percentile in German Residential Electricity Consumption.

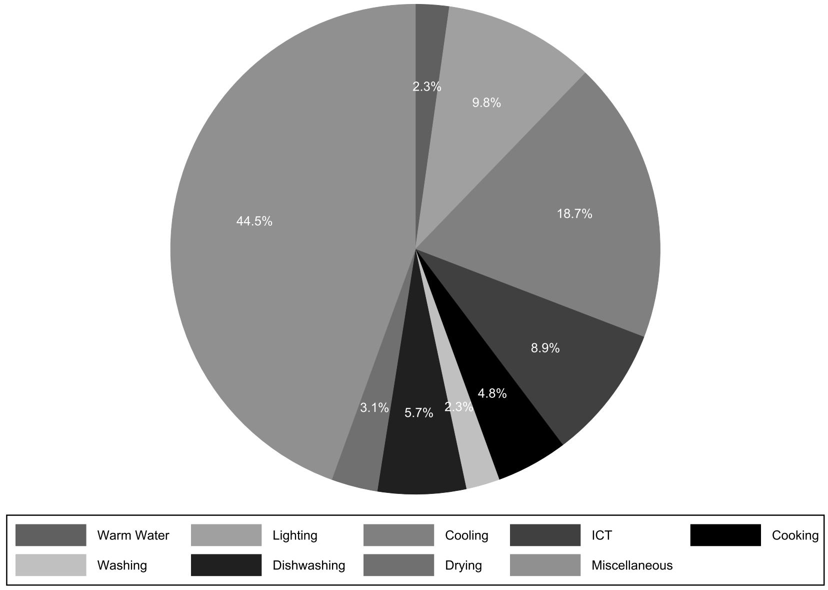

Fig. 6. Shares of diverse End-Use Purposes for the 75th Percentile in German Residential Electricity Consumption.

As there is empirical evidence that only informed consumers respond to rising prices (Jessoe and Rapson, 2014; Frondel and Kussel, 2019), the extent to which higher electricity prices induce reductions in consumption depends on consumers' familiarity with the costs of electricity. In line with Frondel and Kussel (2019), we therefore suggest implementing low-cost information measures on a large scale, such as improving the transparency of tariffs, thereby increasing the salience of prices.

In addition, information campaigns can also encourage efficient application practices that reduce electricity use, such as abstaining from using the standby mode for the television and avoiding the running of partially loaded dishwashers. Yet, to increase the outreach of such information campaigns, their scope needs to be widened. For instance, mandating electricity suppliers to inform their customers about conservation potentials of certain appliances on every bill can effectively reduce electricity demand (Schleich et al., 2013).

Such information campaigns are even more important given the existence of rebound effects, which can reduce the gains from using more energy-efficient appliances by about 20% (Sorrell et al., 2009), notably because the new appliances might be larger and have more functions. Moreover, reductions in electricity consumption can also be partially outweighed by the general trend of decreasing household size and the corresponding loss of economies of scale.

Complementary measures that are targeted at specific appliances can also be availed. Most notably, with respect to appliances that run continually and are thus independent of behavior, such as refrigerators and freezers, consumption reductions can be induced by providing subsidies for the substitution of old, inefficient appliances for more efficient models. For instance, calculations based on our quantile regression results suggest that if high-consumption households replaced both their freezer and their refrigerator by appliances held by low-consumption households, their annual consumption would shrink by about 150 kilowatthours, equivalent to about 4.1% of their consumption or around €45 per year at current electricity prices.

It bears recognizing, however, that the cost-effectiveness of subsidies is predicated on the absence of free-ridership. Thus, prior to implementing any subsidization regime, a thorough ex-ante assessment of the incidence of free-ridership is warranted (e.g. Grösche and Vance, 2009).

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enpol.2019.03.045.

Appendix A

Table A1
Distribution of Household Sizes in both our Sample and in Germany
Source: Destatis (2014).

	Our Sample	Germany (2013)
Household size:		
1 Person household	0.308	0.405
2 Person household	0.422	0.344
3 Person household	0.140	0.125
Household with 4 or more members	0.130	0.126
East Germany	0.193	0.211
Household income > €4700	0.106	0.102
Aged between 18 and 34	0.056	0.192
Aged between 35 and 64	0.588	0.526
Aged 65 and above	0.356	0.282
Non-working	0.432	0.352
Woman	0.309	0.352
Highest school degree	0.380	0.316
Children in household	0.171	0.287

Table A2
Conditional Demand Model for annual Residential Electricity Consumption (in kWh) in which interaction terms are either included or excluded.

	Interaction terms included		Interaction terms excluded	
	Coeff.s	Std. Err.	Coeff.s	Std. Err.
Household Size				
2 Members	666.16*	(267.58)	877.47**	(93.81)
3 Members	2701.01**	(611.07)	1412.33**	(147.75)
4 and more members	1163.82**	(315.85)	1373.11**	(178.21)
Per week absent from home	−11.30	(9.06)	−17.11*	(8.64)
Water heating	477.25**	(129.76)	449.98**	(98.42)
Air-conditioning	−1598.73**	(329.65)	521.93	(465.59)
Per refrigerator	150.56*	(73.68)	291.92**	(74.74)
Per freezer	230.39**	(71.31)	375.39**	(68.88)
Electric oven	122.92	(143.76)	−15.64	(130.93)
Per washing cycle	0.61	(0.45)	0.66	(0.44)
Per dish washing cycle	1.35**	(0.41)	1.53**	(0.40)
Per drying cycles	2.30**	(0.66)	2.66**	(0.60)
Per TV set	131.57**	(48.77)	133.84**	(47.51)
Aquarium or terrarium	689.59**	(169.96)	738.02**	(169.68)
Waterbed	733.47*	(302.30)	496.35*	(216.57)
Sauna	−124.76	(243.52)	272.00	(147.92)
Solarium	1737.86**	(378.94)	345.07	(451.96)
Pond pump	236.77	(163.99)	384.72**	(112.16)
Per computer	73.29	(39.14)	62.22	(38.76)
Per light bulb	0.50	(2.60)	9.16**	(2.85)
Per meal	0.59*	(0.29)	0.45	(0.29)
Constant	1017.53**	(176.91)	708.64**	(177.65)
Interaction Terms	Yes		No	
Number of observations	1292		1292	
R^2	0.5765		0.4825	

Note: ** and * denote statistical significance at the 1% and 5% level, respectively. Robust standard errors are reported. For expositional purposes, coefficient estimates of the interaction terms are not reported.

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