SFB 823

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Nr. 39/2015

Discussion Paper

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Heterogeneity in Residential Electricity Consumption: A Quantile Regression Approach

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Abstract. Reducing household electricity consumption is of central relevance to climate policy given the share of 12.2% of the residential sector in greenhouse gas emissions. Drawing on data originating from the German Residential Energy Survey (GRECS), this paper estimates the contribution of individual appliances to household electricity demand using the conditional demand approach, which relies on readily obtainable information on appliance ownership. Moving beyond the standard focus of mean regression, we employ a quantile regression approach to capture the heterogeneity in the contribution of each appliance according to the conditional distribution of household electricity consumption. This heterogeneity indicates that there are quite large technical potentials for efficiency improvements and electricity conservation in private households. We also 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.

JEL classification: D12, Q41.

Key words: Electricity Consumption, Conditional Demand Approach, Quantile Regression Methods.

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Acknowledgements: We are grateful to the German Association of Energy and Water Industries (Bundesverband der Energie- und Wasserwirtschaft, BDEW) and the German Council for the Efficient Use of Energy (Fachgemeinschaft für effiziente Energieanwendung, HEA) for financial support. This work has also been supported by the Collaborative Research Center "Statistical Modeling of Nonlinear Dynamic Processes" (SFB 823) of the German Research Foundation (DFG), within the framework of Project A3, Dynamic Technology Modeling.

1 Introduction

Germany aims for a 40% reduction of greenhouse gas emissions relative to 1990 by 2020, to be partially met by a 10% reduction in electricity consumption relative to 2008. Several measures are in place to achieve this target, including an eco-tax of 2.05 cents per kilowatt-hour (kWh) on electricity set in 2003, as well as support for the generation of green electricity based on renewable energy technologies via a feed-in tariff system, which was introduced in 2000. The cost of this system is financed by a surcharge on power prices that increased from less than 0.3 cents per kWh in 2001 to 6.17 cents per kWh in 2014 (FRONDEL et al., 2015). Currently, this surcharge accounts for about one fifth of residential electricity prices (BDEW, 2015).

In addition, German households can access general information on electricity saving potential through public programs, which are sometimes coupled with economic incentives for taking part in energy audits and with subsidies for retrofitting equipment like windows and furnaces (GRÖSCHE, VANCE, 2009). The efficacy of such measures depends, of course, on household consumption patterns. However, little empirical evidence exists on the proportion and amount of electricity used for different purposes, nor on the actual extent of saving potentials among private households. To close this void, empirical studies are required that infer a household's total electricity consumption from both the household's stock of electrical appliances and the 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, such empirical studies necessarily resort to econometric methods, such as the widely used conditional demand approach (LARSEN, NESBAKKEN, 2004; DALEN, LARSEN, 2013). This approach includes dummy variables indicating the ownership of electric appliances, such as washing machines and dishwashers, and rests on the idea that the estimated coefficients of the dummies can be interpreted as the mean electricity consumption related to each type of appliance (LARSEN, NESBAKKEN, 2004). Early examples of such studies include PARTI and PARTI (1980), AIGNER et al. (1984)

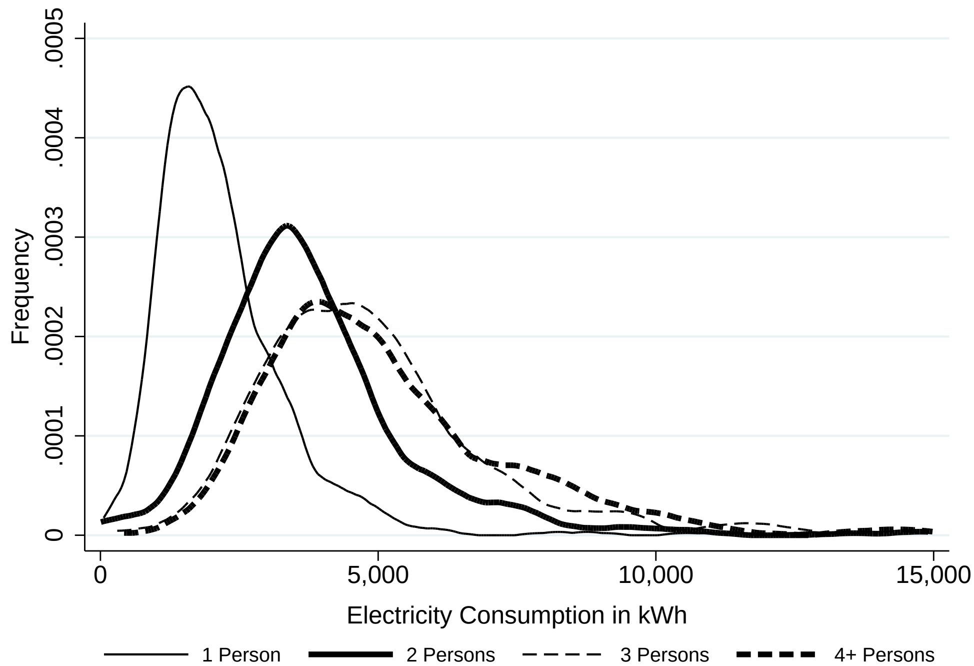
and LAFRANCE and PERRON (1994).

Based on the conditional demand approach (CDA) and a recent survey on the individual stock of electrical appliances among about 2,100 German households, this paper investigates the heterogeneity in household electricity consumption by employing quantile regression methods. Building upon LARSEN and NESBAKKEN (2004) and DALEN and LARSEN (2013), we estimate both the shares of diverse end-use purposes for households located in different parts of households' electricity consumption distribution and bandwidths for the consumption rates of individual appliances, thereby accounting for the variety in household size and user behavior.

Complementing the large body of empirical studies that, in the absence of data on appliance stocks, are forced to rely on socio-economic characteristics (e.g. household size) to explain electricity consumption (e.g. DUBIN, MCFADDEN, 1984), our analysis demonstrates large variation in electricity consumption. As this variation is even evident for households of the same size (Figure 1), it may not only reflect differences in appliance stocks, but also be the result of significant discrepancies in both the consumption rates of the same type of appliances and heterogeneous consumer behavior.

Comparing our mean estimation results for standard electric devices, such as refrigerators, to the consumption levels published by internet portals and consumer protection agencies, we find a relatively tight accordance. Beyond this, the quantile regression approach reveals a spectrum of consumption rates for each type of appliance that covers the whole range from less energy-efficient to highly efficient appliances. This heterogeneity demonstrates that there are quite large technical potentials for efficiency improvements and electricity conservation in private households. Finally, 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. The utility of this approach is further underlined by the importance of the residential sector in Germany: in 2013, the share of private households in total electricity consumption amounted to about 26.0% (AGEB, 2015).

Figure 1: Distribution of Electricity Consumption for various Household Sizes



The following section describes the data set underlying our analysis. Section 3 presents the methodology, followed by a presentation of the results in Section 4. The last section summarizes and concludes.

2 Data

We draw on data obtained from two surveys that were conducted jointly by RWI and the professional German survey institute forsa. The first survey was conducted at the outset of 2014 and gathered data on the electricity consumption of 8,500 private households for the years 2011 to 2013 (RWI, forsa, 2015). Survey respondents were requested to provide detailed information on their electricity bills for these years, as well as on their socio-economic characteristics. From the large pool of households with valid information on their electricity consumption, 2,100 were randomly selected to be interviewed in a second survey that followed in mid-2014. Its 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 (Figure 1), which obviously increases with the number of household members. In fact, the distribution of consumption exhibits the lowest variation for single-person households, while the spread is much larger for households with four and more members ("4+ Persons"). It bears noting that with shares of about 31% and 42%, respectively, single- and two-person households represent the overwhelming majority of our sample households, whereas households with three and more members are relatively rare (Table 2). Compared to the German population, single-person households are slightly underrepresented in our sample, while two-person households are somewhat overrepresented (Table A1 in the appendix). 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.

Figure 1 also shows that the kernel densities are not symmetric, but skewed to the right. That is, there are only a few households exhibiting consumption levels that are substantially higher than the average consumption of households of the same size. As is typical for distributions that are skewed to the right, mean consumption levels are higher than the median values for all household sizes (Table 1). Overall, the mean consumption amounts to about 3,650 kWh, whereas the median is somewhat smaller, at 3,300 kWh. Table 1 reconfirms that consumption increases with the number of household members: median values vary between 2,000 kWh for single households and 4,600 kWh for households with four and more members. Both increasing standard deviations from the mean, as well as the large variation of mean and median values with respect to household size, support the impression that residential electricity consumption is very heterogeneous.

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). Among the other behavioral covariates that affect consumption is the number of washing cycles in the four weeks before completing the survey. This information is extrapolated to the period of one year to gauge the annual electricity consumption

Table 1: Average Electricity Consumption (in kWh) for Households of Various Sizes in 2013

Household Size	Number of Observations	Mean	Std. Dev.	Median
1 Member	649	2,225.4	1,416.4	1,957.0
2 Members	889	3,835.5	1,843.9	3,528.0
3 Members	294	4,850.1	2,018.8	4,561.0
4 and more Members	273	5,113.0	2,197.0	4,568.5
Overall	2,105	3,646.5	2,089.0	3,302.0

for cloth 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 present among German households than washing machines and dishwashers. These devices are also used more frequently than tumble dryers, which, on average, are employed nearly 100 times a year conditional on ownership (Table 2).

Gathering data on the utilization of appliances may be prone to large uncertainties. For instance, it is unlikely that a respondent of a multi-person-household is able to provide reliable information on the time spent watching television 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, e.g., the number of hours that a TV set is running every day.

Other household appliances, such as refrigerators and freezers, whose mean ownership is 1.4 and 0.7, respectively, run the whole day and permanently need electricity. Thus, it should suffice to count the number of such devices that are available in a household. The same applies to swimming pools, aquaria and terraria, although these are less common in German households. Other uncommon, but not permanently employed appliances are air conditioners, saunas, waterbeds, and solaria. Much more common are TVs, electric ovens, computers and laptops: on average, virtually each German household possesses a laptop, a computer, and an electric oven.

The appliances presented in Table 2 undoubtedly represent only a limited set

Table 2: Summary Statistics

Variables	Type	Mean	Std. Dev.	Number of Observations
1 Person Household	Dummy	0.308	–	2,105
2 Person Household	Dummy	0.422	–	2,105
3 Person Household	Dummy	0.140	–	2,105
Household with 4 and more Members	Dummy	0.130	–	2,105
Weeks Absent from Home	Count	3.53	4.52	1,996
Dishwasher	Dummy	0.824	–	2,079
Number of washing cycles per year	Count	185.82	112.31	1,674
Washing machine	Dummy	0.958	–	2,098
Number of washing cycles per year	Count	184.52	147.43	1,991
Tumble Dryer	Dummy	0.556	–	2,098
Number of drying cycles per year	Count	98.21	98.06	1,130
Refrigerators	Count	1.35	0.576	2,050
Freezers	Count	0.72	0.639	2,085
TV sets	Count	1.73	0.886	2,054
Computer	Count	0.94	0.815	2,099
Laptops	Count	1.00	0.906	2,099
Light bulbs	Count	25.11	15.92	1,971
Meals	Count	317.84	136.78	2,100
Electric oven	Dummy	0.941	–	2,079
Aquarium or Terrarium	Dummy	0.062	–	2,094
Waterbed	Dummy	0.041	–	2,094
Sauna	Dummy	0.075	–	2,094
Home automation system	Dummy	0.205	–	2,094
Pond pump	Dummy	0.160	–	2,094
Water heating	Dummy	0.176	–	2,093
Air-conditioning	Dummy	0.004	–	2,106
Swimming pool	Dummy	0.001	–	2,094
Solarium	Dummy	0.012	–	2,094

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 including further dummy variables for these and other appliances in our estimations, the associated electricity consumption is captured by incorporating the household size dummies. As the number of small appliances differs across households of various sizes, it is plausible to assume distinct coefficients for the household size dummies.

3 Methodology

The conditional demand approach (CDA) employs data on appliance stocks to quantify the effect of a certain appliance on the electricity consumption level, conditional on possessing this appliance. In CDA studies (e.g. DALEN, LARSEN, 2013; HSIAO et al., 1995; HALVORSEN, LARSEN, 2001; LARSEN, NESBAKKEN, 2004; REISS, WHITE, 2005), dummy variables D_{ij} play a key role in explaining the electricity consumption y_i of an individual household i, where D_{ij} equals unity if household i possesses appliance j or executes activity j and is zero otherwise. Our point of departure in estimating the determinants of electricity consumption largely follows DALEN and LARSEN (2013), with the modification that we include variables N_{ik} that count the number of appliance types, such as the number of TV sets and notebooks:

$$y_i = y_0 + \sum_{j=1}^{J} \gamma_j D_{ij} + \sum_{k=1}^{K} \theta_k N_{ik} + \sum_{j=1}^{J} \sum_{m=1}^{M} \rho_{jm} (C_{im} - \bar{C}_{jm}) D_{ij} + \varepsilon_i, \tag{1}$$

with γ_j, θ_k, and ρ_{jm} being parameters to be estimated and ε_i denoting a stochastic error term. The variables C_{im} ($m = 1, 2, ..., M$) represent household characteristics, such as the number of household members, and $\bar{C}_{jm}$ designates the mean value of these variables for those households that possess appliance j. The parameter γ_j reflects the mean electricity consumption with respect to end use j given that the household characteristics C_{im} are all equal to the respective variable means calculated over all households for which end use j is relevant or given that $\rho_{jm} = 0$ for all m, that is, no household characteristics are relevant for end use j by definition. Typically, though, individual household characteristics equal the sample means only by chance and, hence, the interaction term generally does not vanish.

Commonly, Equation 1 is estimated using Ordinary (OLS) or Generalized Least Squares (GLS) methods, which focus on estimating the conditional expectation function (CEF), $E(y_i|\mathbf{x}_i)$, thereby yielding a uniform effect of each variable embodied in $\mathbf{x}$ (FRONDEL et al., 2012). To provide a more complete picture of the relationship between electricity consumption y and its determinants at different points in the conditional distribution of y, we additionally employ the quantile regression approach that allows for more flexibility in the estimation of the appliances' effect on the residential electricity consumption level in that it enables us to estimate a range of conditional quantile functions (CQF) $Q_\tau(y_i|\mathbf{x}_i)$:

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

where τ specifies the quantile in the distribution of electricity consumption and may take on values between zero and unity and $\boldsymbol{\alpha}_{\mathbf{x}}(\tau)$ indicates the varying effect of holding a certain device 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. In short, the most attractive feature of the quantile regression method is that it generally provides for a richer characterization of the data than OLS, as quantile methods allow us to study the impact of a regressor on the full distribution of the dependent variable, not just the conditional mean.

For $\tau = 0.5$, for instance, $Q_{0.5}(y|\mathbf{x})$ designates the median of electricity consumption conditional on the set of covariates $\mathbf{x}$. In this special case, estimates of the parameters of quantile regression model 2 result from the minimization of the sum of the absolute deviations, $|Q_{0.5} - \widehat{Q}_{0.5}|$, where $\widehat{Q}_{0.5}$ denotes the prediction for the dependent variable based on the median regression. This is perfectly in line with the well-known statistical result that it is the median that minimizes the sum of absolute deviations of a variable, whereas it is the mean that minimizes the sum of squared residuals. It is also well-known that the median is more robust to outliers than the mean. In a similar vein, quantile regressions also have the advantage that they 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.

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

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

where underpredictions $r_i := Q_\tau(y_i|\mathbf{x}_i) - \widehat{Q}_\tau(y_i|\mathbf{x}_i) > 0$ 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 $\widehat{Q}_\tau$ 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

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

where $r := Q_\tau - \widehat{Q}_\tau$ and the indicator function $1(r>0)$ indicates positive residuals r and $1(r \leq 0)$ 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 is set up as a linear programming problem and can thus be solved by linear programming techniques (KOENKER, 2005). Variances can be estimated using a method suggested by KOENKER and BASSETT (1982), but bootstrap methods are often preferred and are used here.

Conditional on x, the CQFs given by Equation 2 depend on the distribution of ε_{it} via $F_{\varepsilon_i}^{-1}(\tau)$. In the special case that errors are independent and identically distributed, that is, if $F_{\varepsilon_i}^{-1}(\tau) = F_{\varepsilon}^{-1}(\tau)$ and, hence, the inverse distribution function does not vary across observations, the CQFs exhibit common slopes $\boldsymbol{\alpha}_{\mathbf{x}}(\tau) = \boldsymbol{\alpha}_{\mathbf{x}}$, differing only in the intercepts: $\alpha(\tau) + F_{\varepsilon_i}^{-1}(\tau)$. In this case, there is no need for quantile regression methods if the focus is on marginal effects, as these are given by the invariant slope parameters. In general, however, the CQFs' Q_τ will differ at different values τ in more than just the intercept and may well be even non-linear in x. This may be the case if, for example, errors are heteroscedastic.

4 Results

Upon estimating Equation 1 via OLS, we find that virtually none of the coefficients ρ_{jm} of the interaction terms of the appliance dummies D_{ij} and the household characteristics C_{im} are statistically different from zero. In addition, the inclusion of these interaction terms has only a negligible bearing on the other coefficient estimates (results are available upon request). For exposition purposes, we consequently present only those results of the OLS and quantile regressions in which no interaction effects are included.

The OLS regression results presented in the first column of Table 3 suggest that the highest consumption figures refer to appliances that are less common among German households. 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 and 400 kWh for freezers.

While the survey of 2014 focused on household appliances with significant consumption rates, many appliances could not have been included in our regressions. One reason is that respondents are uncertain about the prevalence of certain types of appliances, such as a recirculation pump. Moreover, the data collection for appliances with low consumption rates, such as the number of electric tooth-brushes, 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. It turns out that their estimates increase in magnitude with larger household sizes. For instance, the OLS estimate of the residual value for two-person households is about 830 kWh higher than that for single-person households (Table 3). Three- and four-person households exhibit an even higher residual value, although the difference between the OLS estimates for these two household sizes is not statistically significant. These residual consumption values generally differ, because both the number and the size of the excluded appliances tend to increase with household size.

Due to the lack of data, we cannot control for the size, type, wattage and utilization of all these appliances. As a consequence, the OLS coefficient estimates refer to an appliance of average size, efficiency and utilization. For example, the annual electricity consumption of a typical sample TV set amounts to 114 kWh while that of a typical sample computer is about 150 kWh per year.

It bears noting that many of our OLS estimates are in line with consumption data provided by consumer information centers and online information portals. For instance, although the 400 kWh electricity consumption of a typical sample freezer is somewhat higher than the 270 kWh reported by the Council for the efficient use of energy (Fachgemeinschaft für effiziente Energieanwendung, HEA, 2011), there are plausible reasons for this discrepancy. For starters, freezers of the sample households are older and, hence, less energy-efficient than those analyzed by HEA, which are limited to new models with efficiency label A and a volume of 200 liters. By contrast, more than one third of our sample households stated that their freezers are more than 10 years old. Differences in the size of freezers may be another reason for this discrepancy.

In the absence of data on the size, age, and efficiency label of appliances, these differences may alternatively be captured by employing a quantile regression approach. With this approach, we generally find that the coefficient estimates for the appliances of households from the lower tail of the electricity consumption distribution are smaller than those of the households from the upper tail (Table 4), implying that the consump-

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

	OLS Regression		Median Regression	
	Coeff.s	Std. Err.s	Coeff.s	Std. Err.s
Household Size				
2 Members	834.2**	(83.75)	710.0**	(68.71)
3 Members	1,370.0**	(130.07)	1,244.4**	(123.82)
4 and more members	1,356.5**	(160.83)	1,164.5**	(149.78)
Per week absent from home	-21.2**	(7.9)	-17.2**	(4.7)
Water heating	466.8**	(88.4)	512.3**	(69.8)
Air conditioning	481.9	(459.5)	465.7	(444.0)
Per refrigerator	303.2**	(66.4)	374.5**	(53.6)
Per freezer	402.4**	(61.5)	445.0**	(48.2)
Electric oven	108.1	(112.8)	103.5	(96.5)
Per washing cycle	0.68	(0.4)	0.46*	(0.2)
Per dish washing cycle	1.27**	(0.4)	1.45**	(0.3)
Per drying cycle	2.79**	(0.5)	2.84**	(0.5)
Per TV set	113.8**	(42.2)	134.4**	(36.7)
Aquarium, terrarium	761.3**	(157.0)	808.7**	(205.1)
Waterbed	512.2*	(222.3)	346.7	(187.1)
Sauna	264.8	(149.2)	163.1	(159.0)
Swimming pool	1,907.8**	(413.1)	1,660.8	(2,088.6)
Solarium	402.5	(515.6)	373.6	(514.5)
Home automation system	15.1	(84.5)	89.8	(77.3)
Pond pump	365.4**	(102.6)	379.3**	(75.1)
Per computer	147.8**	(49.9)	216.0**	(42.5)
Per laptop	8.19	(43.4)	52.6	(37.0)
Per light bulb	10.22**	(2.7)	4.75	(2.5)
Per meal	0.40	(0.3)	0.26	(0.2)
Constant	626.4**	(160.4)	429.0**	(135.8)

*Note: Robust standard errors are reported; * denotes significance at the 5% level, ** at the 1% level. Number of observations used for estimation: 1,653.*

tion rates of appliances are higher among households with a large electricity consumption.

Table 4: OLS- and Quantile Regression Results for Residential Electricity Consumption (in kWh)

			Percentiles		F-Test for Equality
	OLS	10th	50th	90th	of Coefficients
	Coeff.s	Coeff.s	Coeff.s	Coeff.s	
Household Size					
2 Members	834.2**	419.6**	710.0**	1,126.5**	8.53**
3 Members	1,370.0**	848.9**	1,244.4**	1,773.2**	8.27**
4 and more members	1,356.5**	922.0**	1,164.5**	1,862.7**	4.76*
Per week absent from home	-21.2**	-38.6**	-17.2**	-12.7	1.40
Water heating	466.8**	266.2**	512.3**	615.8*	0.16
Air conditioning	481.9	-616.2**	465.7	1,205.5*	0.48
Per refrigerator	303.2**	322.5**	374.5**	391.9**	0.19
Per freezer	402.4**	248.8**	445.0**	534.8**	0.20
Electric oven	108.1	252.6*	103.5	-77.9	4.01*
Per washing cycle	0.68	0.37	0.46*	-0.27	0.07
Per dish washing cycle	1.27**	1.52**	1.45**	1.98**	1.82
Per drying cycle	2.79**	2.40**	2.84**	3.07**	3.96*
Per TV set	113.8**	93.0**	134.4**	118.2	3.40
Aquarium, terrarium	761.3**	549.9**	808.7**	1,219.4**	0.19
Waterbed	512.2*	253.2	346.7	1,180.1**	0.16
Sauna	264.8	391.7**	163.1	565.6**	0.32
Swimming pool	1,907.8**	2,531.2**	1,660.8	197.3	0.85
Solarium	402.5	-157.0	373.6	2,102.3	0.10
Home automation system	15.1	16.7	89.8	-53.5	1.80
Pond pump	365.4**	312.7**	379.3**	470.2**	2.38
Per computer	147.8**	58.2	216.0**	174.9*	9.09**
Per laptop	8.19	-28.3	52.6	5.2	2.98
Per light bulb	10.22**	4.64*	4.75	32.6**	14.11**
Per meal	0.40	-0.07	0.26	0.85*	2.77
Constant	626.4**	172.3	429.0**	1,118.3**	9.03**

*Note: Robust standard errors are reported; * denotes significance at the 5% level, ** at the 1% level. Number of observations used for estimation: 1,653.*

For example, according to our quantile regression results, for freezers of households from the 10th percentile, that is, households with a very low electricity consumption, the consumption rate estimate amounts to 250 kWh, which is close to the reference value of 270 kWh reported by HEA (2011) for new, energy-efficient freezers. This seems plausible when considering that the efficiency level of appliances is an important factor in determining how much electricity a household consumes.

Another example for the good accordance of our results with the consumption values published elsewhere is the electricity consumption of washing cycles. Both our OLS and quantile regression results fit well to the interval of consumption values reported in Table 5 for 10-years old washing machines. The OLS estimate of almost 0.7 kWh per cycle (Table 3) is somewhat higher than the value reported for a washing temperature of 40°C, while the estimates of 0.37 and 0.49 kWh for the 10th and 50th percentile (Table 4) are in line with the values for washing temperatures between 30 and 40°C (Table 5).

Table 5: Electricity Consumption of a 10 years old Washing Machine depending on the Temperature Choice

Temperature	30 °C	40 °C	60 °C	90 °C
Electricity Consumption in kWh	0.4	0.6	1.1	1.8

Source: VÖ *(2012)*

There are many other examples for a confirmatory reality check of our estimation results. A final comparison noted here is with the values reported in Table 6 for TV sets of different efficiency levels. While the OLS estimate of 114 kWh lies between the reference values for a TV set with an efficiency level B and an old, inefficient set, the estimate from the 10th percentile of 93 kWh fits well to the B level of 88 kWh.

Table 6: Electricity Consumption of TV Sets

Efficiency Class	A+	B	Old Set
Electricity Consumption in kWh	60	88	159

Source: VÖ *(2012)*

Turning to the heterogeneity in the results across quantiles, we find substantial differences across variables and appliances, not least the household size indicators (Table 4). In fact, the F tests on the equality of the coefficients for the 10th and the 90th percentile of the consumption distribution, presented in Column 5 of Table 4, indicate statistically significant differences for all household sizes. Stark discrepancies in consumption rates can also be observed for energy-intensive appliances such as waterbeds, as well as the electricity consumption per light bulb. For instance, for households belonging to the 10th percentile of the electricity consumption distribution, an additional light bulb increases consumption by merely about 5 kWh, whereas for households at the 90th percentile the effect of an additional bulb is larger than 30 kWh.

The heterogeneity in the electricity consumption of light bulbs becomes even more apparent from Figure 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 Figure 2, the appealing character of quantile regression methods is also revealed by Figure 3, as it shows that households at the 10th percentile typically possess freezers that exhibit a low consumption rate of about 250 kWh per annum (Table 4), whereas freezers of households at the 90th percentile need about twice as much electricity. Similar pictures can be drawn for other appliances.

Using the OLS and quantile regression estimates reported in Table 4, we now calculate the shares of electricity consumption that can be attributed to diverse end-use purposes, such as cooling and dishwashing. Following closely DALEN and LARSEN (2013), we first employ the mean values for the frequency of an appliance type in the sample, $\bar{D}_j$, and the corresponding OLS consumption estimate, $\widehat{\gamma}_j$, and multiply both to predict the mean electricity consumption of appliance j for average households for which, by definition, the interaction term in Equation 1 vanishes. The predicted mean consumption of appliance j therefore reads: $\gamma_j^p = \widehat{y}_j \bar{D}_j$.

The predicted end-use share of appliance j is then given by $s_j^p := \frac{y_j^p}{\bar{y}}$, where $\bar{y} := \frac{1}{N} \sum_{i=1}^{n} y_i$ denotes the mean electricity consumption of a household calculated from the observed consumption values of our sample households. In a similar vein, for ap-

Figure 2: Quantile Regression Results for the Electricity Consumption Rates of Light Bulbs

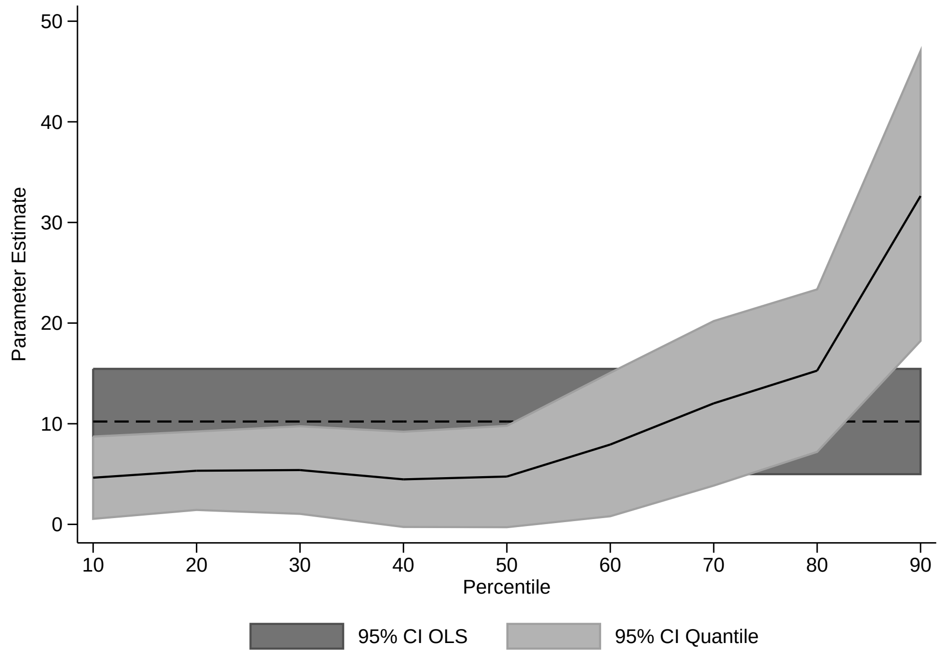
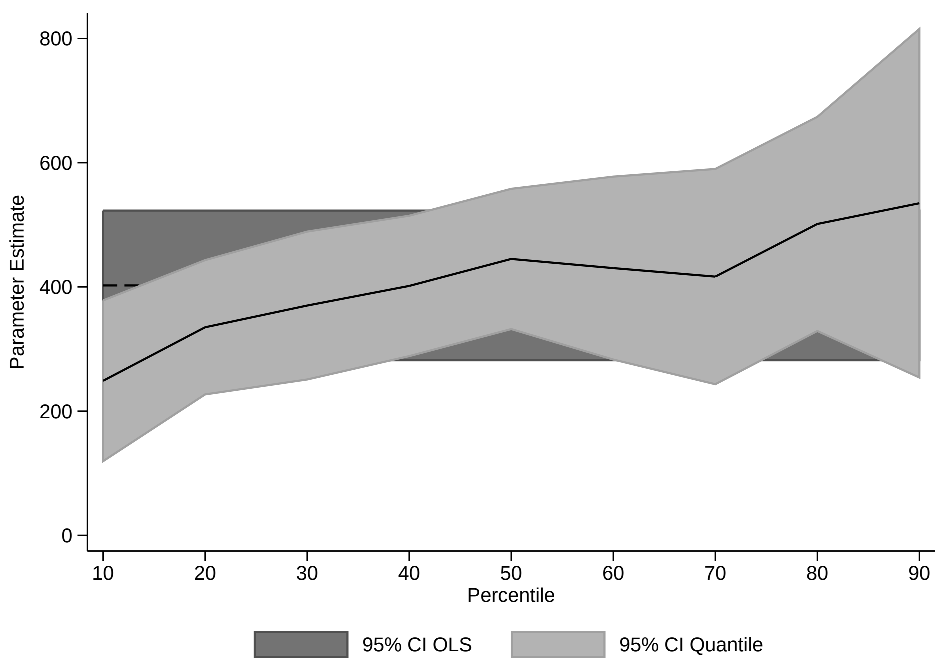


Figure 3: Quantile Regression Results for the Electricity Consumption Rates of Freezers



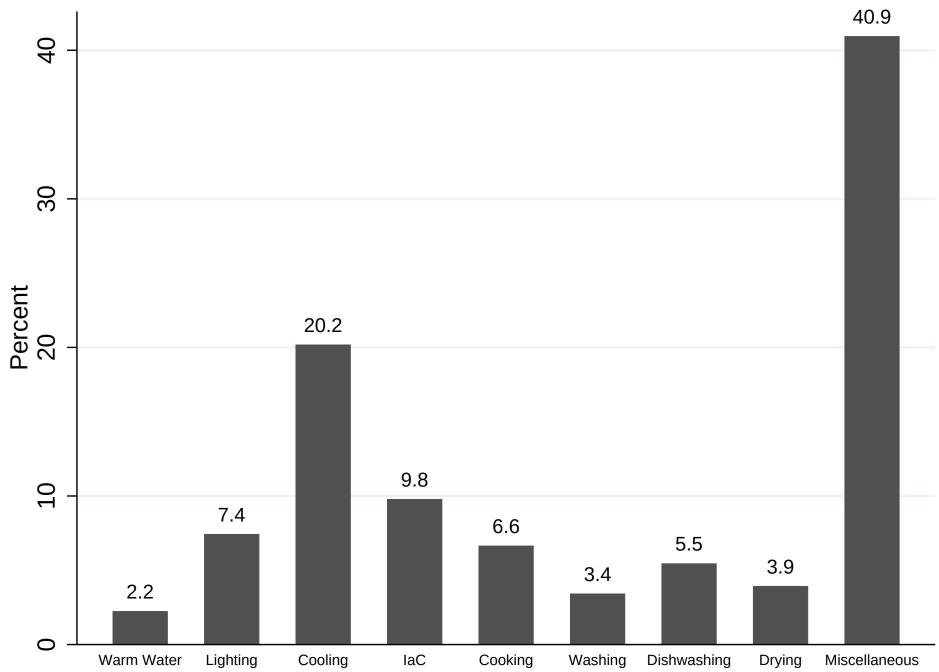
pliances for which their number N_{ik} is employed as a regressor, the end-use share is given by $s_k^p := \frac{y_k^p}{\bar{y}}$, where $y_k^p = \widehat{\theta}_k \bar{N}_k$ and $\widehat{\theta}_k$ denotes the corresponding OLS consumption estimate and $\bar{N}_k = \frac{1}{N} \sum_{i=1}^{n} N_{ik}$ designates the mean number of appliance type k in the sample.

The results of this exercise are presented in Figure 4. Note that heating purposes do not appear in this and the following figures, as households solely heating with electricity are not included in the survey of 2014 due to the fact that, in contrast to other countries, such as France and Norway, solely heating with electricity is not common in Germany. In fact, according to the German Residential Energy Consumption Surveys (GRECS), the share of these households is less than 5% (RWI, forsa, 2015).

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). Because of this rather low frequency, the mean share of water heating is as low as 2.2% in the total electricity consumption of average households. By contrast, with a share of about 20%, cooling purposes play a major 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-conditioning, although this appliance is rarely present in German households: only 0.4% of our sample households employ air-conditioning devices (Table 2).

With almost 41%, miscellaneous purposes by far account for the largest share in electricity consumption. This share, which almost exactly fits to that reported by DALEN and LARSEN (2013) for Norwegian households for the year 2006, includes all end uses that are not explicitly attributed to the categories displayed in Figure 4. In fact, the miscellaneous share is based on the estimate of the constant, the coefficient estimates of the household size dummies, as well as the estimates for the coefficients of the less common appliances, that is, aquarium/terrarium, waterbed, sauna, home automation system, pond pump, swimming pool and solarium. Another increasingly important purpose of electricity demand is for information and communication (IaC), which encompasses here the consumption of personal computers, laptops, and television sets. The respective share amounted to about 10% in 2013.

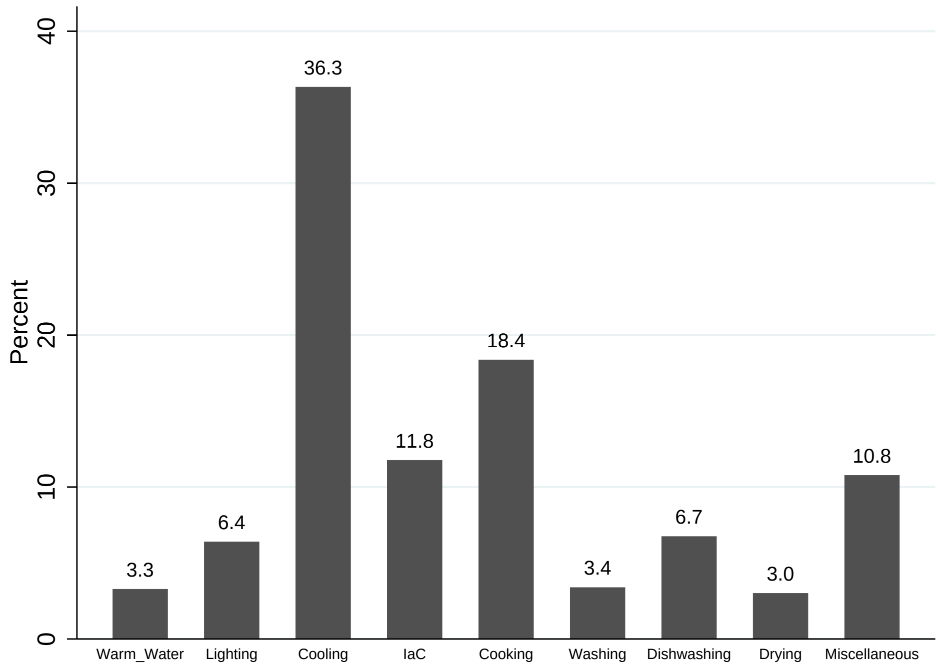
Figure 4: Mean Shares in Electricity Consumption of diverse End-Use Purposes for the German Residential Sector in 2013



Of course, the importance of diverse purposes varies across household types. This becomes evident from our quantile regression results and the following figures for households originating from the 10th and 90th percentiles in the residential electricity consumption distribution. For instance, for households that belong to the 10th percentile, the shares of 36.3% and 18.4% for cooling and cooking purposes, respectively (Figure 5), are much more pronounced than those for households belonging to the middle of the electricity distribution (Figure 4). On the other hand, the miscellaneous share of 10.8% shrinks dramatically for these households relative to the mean value of almost 41% (Figure 4). Apparently, for these households end-use purposes that are essential for daily life are of highest importance. [1]

[1] Indeed, our data suggest that the likelihood of owning non-essential appliances is low among households with low consumption rates. For instance, belonging to the 10th percentile of the electricity consumption distribution reduces the likelihood of possessing a home automation system by 15% and even by 25% in the case of pond pumps. On the other hand, according to our data, electricity consumption increases by roughly 280 kWh for every 500 Euro of additional income. This allows households to purchase non-essential appliances that are not explicitly covered by the end-use categories. However, households could deliberately refrain from purchasing such appliances for electricity conservation purposes or other motivations. Future research should cover these issues.

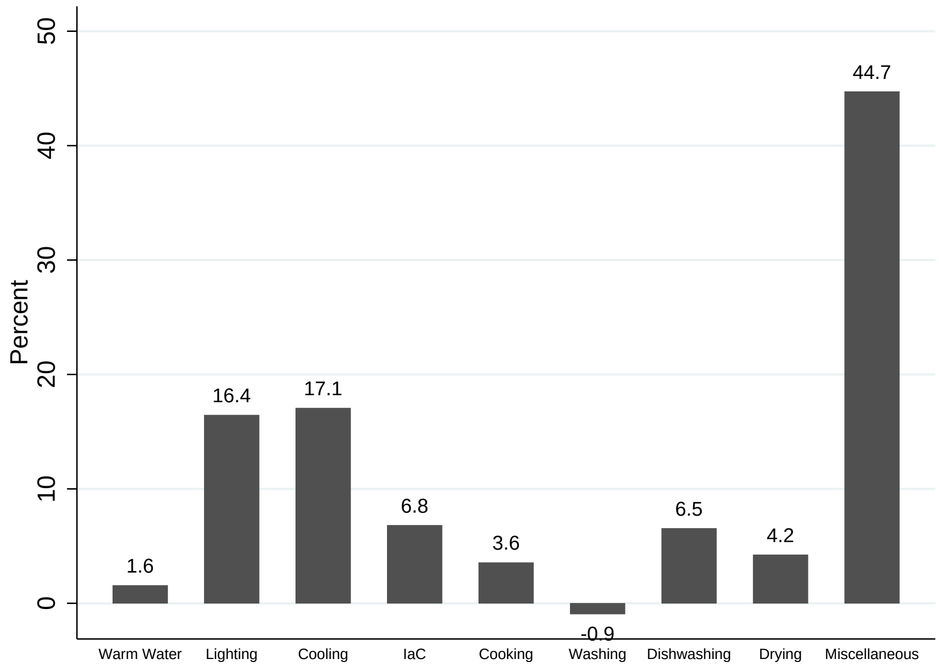
Figure 5: Shares of diverse End-Use Purposes in 2013 for the 10th Percentile in German Residential Electricity Consumption.



A rather different picture emerges for households belonging to the 90th percentile of electricity consumption (Figure 6). Cooling and cooking purposes assume a notably smaller significance than in households of the 10th percentile, while the miscellaneous share of 44.8% is somewhat higher than the respective mean share. Likewise, with a share of 16.4%, lighting purposes appear to be more relevant in households with a large electricity consumption than in average households or those 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, where these shares are estimated in a similar fashion as the mean shares: Instead of the OLS estimates, the coefficient estimates for the respective quantile regressions are employed for calculating the end-uses shares, as well as the appliance shares of households belonging to the respective percentile. For example, for households belonging to the 90th percentile, for each end-use purpose we have calculated the share of the corresponding appliances that emerge from households with electricity consumptions equal to or

Figure 6: Shares of diverse End-Use Purposes in 2013 for the 90th Percentile in German Residential Electricity Consumption.



higher than the 90th percentile.

5 Summary and Conclusions

This paper has employed the conditional demand approach to econometrically estimate the contribution of common household appliances to electricity demand from a sample of about 2,100 German households. We find that our mean (OLS) estimates for appliances such as refrigerators and freezers are in close correspondence with those published by consumer agencies and internet portals.

Moving beyond the standard focus of estimating mean effects, we have applied quantile regression methods, which allow for capturing heterogeneity in the coefficients across quantiles of the electricity consumption distribution. After all, it is to be expected that even if households were able to precisely measure their electricity demand using measurement devices, a challenge in its own right from a surveying perspective, there would still be a large variation in the consumption rates of particular appliance types.

Incorporating dummy or count variables for each appliance type and estimating their influence with the quantile methods applied here affords considerably more tractability, obviating the need to measure the contribution of each individual appliance to overall electricity demand. In the end, 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.

Appendix

Table A1: Distribution of Household Sizes in both our Sample and in Germany

	Our Sample		
Household Size	Western Germany	Eastern Germany	Overall
1 Person	29.8%	35.2%	30.8%
2 Persons	42.1%	42.9%	42.2%
3 Persons	14.1%	13.3%	14.0%
4+ Persons	14.0%	8.6%	13.0%
	100.0%	100.0%	100.0%
	Germany (2013)		
1 Person	39.7%	43.5%	40.5%
2 Persons	34.1%	35.8%	34.4%
3 Persons	12.5%	12.4%	12.6%
4+ Persons	13.7%	8.3 %	12.5%
	100.0%	100.0%	100.0%

Source: DESTATIS *(2014)*

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