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Manuel Frondel, Stephan Sommer, and Colin Vance[1]

Heterogeneity in Residential Electricity Consumption: A Quantile Regression Approach

Abstract

Drawing on the most recent wave of the German Residential Energy Survey (GRECS), this paper estimates the contribution of individual appliances to household electricity consumption. Moving beyond the standard focus of estimating mean effects, we combine the conditional demand approach with quantile regression methods to capture the heterogeneity in the contribution of each appliance to the distribution of household electricity consumption. While reflecting correlations, rather than causal relationships, our results indicate 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

Keywords: Electricity consumption; conditional demand approach; quantile regression methods

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1 Manuel Frondel, RWI, and RUB; Stephan Sommer, RWI; Colin Vance, RWI and Jacobs University Bremen. – *We are grateful to the German Association of Energy and Water Industries (BDEW) and the German Council for the Efficient Use of Energy (HEA) for financial support and participants of the EAERE Conference 2016 in Zurich, Switzerland, for helpful comments and suggestions. Furthermore, we gratefully acknowledge financial support by the Federal Ministry of Education and Research (BMBF) under grant 03SFK4B0 (Kopernikus Project ENavi). 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 Project A3, Dynamic Technology Modeling. –* *All correspondence to: Manuel Frondel, RWI, Hohenzollernstr. 1-3, 45128 Essen, Germany, e-mail: manuel.frondel@rwi-essen.de*

1 Introduction

Little empirical evidence exists on the proportion and amount of electricity used for different purposes. 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, empirical studies necessarily resort to econometric methods, such as the widely used conditional demand approach (LARSEN, NESBAKKEN, 2004; DALEN, LARSEN, 2015). This approach includes dummy variables indicating 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 (LARSEN, NESBAKKEN, 2004). Early examples of such studies include PARTI and PARTI (1980), AIGNER et al. (1984) and LAFRANCE and PERRON (1994).

Based on a unique data set originating from both the most recent wave of the German Residential Energy Survey (GRECS) and a recent survey on the individual stock of electrical appliances among a sub-sample of about 2,100 German households of the GRECS panel, this paper investigates the heterogeneity in household electricity consumption by combining the conditional demand approach (CDA) with quantile regression methods. Building upon LARSEN and NESBAKKEN (2004) and DALEN and LARSEN (2015), we estimate both the shares of diverse end-use purposes for households located in different parts of the household electricity consumption distribution, as well as bandwidths for the consumption rates of individual appliances, thereby accounting for both user behavior and the heterogeneity in electric appliance stocks of households.

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

Indeed, our 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. While our 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.

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 and of end-use shares in Section 5. The last section summarizes and concludes.

2 Data

We draw on data obtained from two related surveys that were conducted jointly by RWI and the professional German survey institute forsa. As part of the German Residential Energy Survey (GRECS) that was established in 2005 (RWI, forsa, 2005), a survey that took place at the outset of 2014 gathered data on the annual electricity consumption of 8,500 private households for the years 2011 to 2013, as well as socio-economic household characteristics, such as household size (RWI, forsa, 2015). Among other issues, survey respondents were requested to provide detailed information on their electricity bills for the years 2011 to 2013, including electricity prices per kWh, fixed fees, and the households' electricity consumption in the respective billing periods.

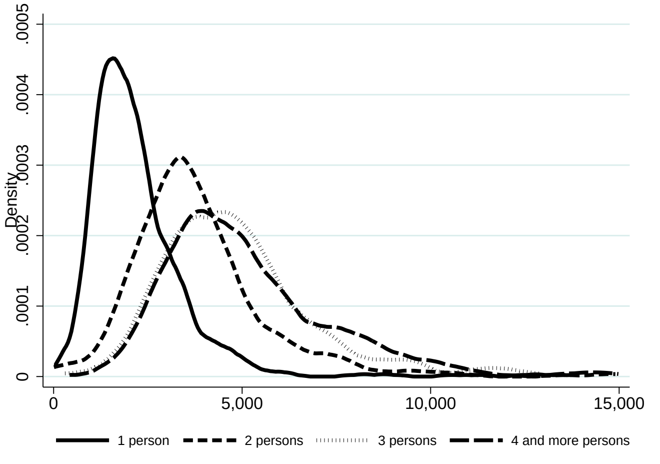
Using the starting and ending date of the billing period and the households' individual electricity consumption in kWh, we are able to calculate a household's average consumption per day and infer its annual electricity consumption by multiplying the daily average by 365 days. In this respect, the GRECS strongly contrasts with the Consumer Expenditure Surveys of the US and UK, in which survey respondents provide the monetary amount spent on electricity, rather than consumption data in kWh. In the US and UK surveys, consumption levels are instead imputed using the average price in the respondents' area (FELL, LI, PAUL, 2014). This method yields less precise information on individual consumption than the GRECS.

While it is difficult to distinguish outliers and misinformation from true consumption values, we generously sacrifice those household observations that exhibit very large per-capita consumption levels and employ an iterative procedure that in each iteration step drops all those values that deviate from the mean per-capita consumption level by more than the twofold of the standard deviation. Mean per-capita consumption levels and standard deviations are recalculated in each iteration step, with the procedure coming to an end when no observations are dropped anymore. From the large pool of several thousand households with plausible information on their electricity consumption that is validated in this way, about 2,100 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 our 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, supporting the impression that residential electricity consumption is very heterogeneous.

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 households, whereas households

Figure 1: Distribution of Electricity Consumption for various Household Sizes in 2013



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). 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). 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 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

Table 1: Summary Statistics of Socioeconomic Characteristics

	Mean	Std. Dev.	Number of observations
1 Person household	0.309	–	2,106
2 Person household	0.422	–	2,106
3 Person household	0.140	–	2,106
Household with 4 or more members	0.130	–	2,106
Age (in years)	58.0	12.8	2,106
East Germany	0.193	–	2,106
Household net income (in euros)	2,800	1,293	1,968
Full-time employed	0.435	–	2,077
Part-time employed	0.133	–	2,077
Unemployed	0.432	–	2,077
Property owner	0.674	–	2,106
Single-family house	0.442	–	2,101
Duplex house	0.172	–	2,101
Apartment building	0.386	–	2,101
Female	0.309	–	2,106
Living area (in square meters)	113.7	48.9	2,103
High school degree	0.255	0.436	2,100
# Children in household	0.282	0.688	2,085
Electricity price (in Cents per kWh)	22.7	6.4	1,743
Electricity consumption (in kWh per year)	3,596	1,898	2,070

nearly 100 times a year conditional on ownership (Table 2).

Gathering data on the utilization of some 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, for example, the number of hours that a TV set is running every day.

Other household appliances, such as refrigerators and freezers, whose mean number per household amounts to 1.35 and 0.72, 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

Table 2: Summary Statistics of Electric Appliances and their Usage

Variables	Type	Mean	Std. Dev.	Number of Observations
# Weeks absent from home	Count	3.53	4.52	1,996
Water heating	Dummy	0.176	–	2,093
Dishwasher	Dummy	0.824	–	2,079
# washing cycles per year	Count	185.8	112.3	1,674
Washing machine	Dummy	0.958	–	2,098
# washing cycles per year	Count	184.5	147.4	1,991
Tumble Dryer	Dummy	0.556	–	2,098
# drying cycles per year	Count	98.2	98.1	1,130
Electric oven	Dummy	0.941	–	2,079
# Meals	Count	317.8	136.8	2,100
# Refrigerators	Count	1.35	0.58	2,050
# Freezers	Count	0.72	0.64	2,085
# TV sets	Count	1.73	0.89	2,054
# Personal computers	Count	0.94	0.82	2,099
# Laptops	Count	1.00	0.91	2,099
# Light bulbs	Count	25.11	15.92	1,971
Aquarium or Terrarium	Dummy	0.062	–	2,094
Waterbed	Dummy	0.041	–	2,094
Sauna	Dummy	0.075	–	2,094
Pond pump	Dummy	0.160	–	2,094
Air-conditioning	Dummy	0.044	–	2,106
Swimming pool	Dummy	0.001	–	2,094
Solarium	Dummy	0.012	–	2,094

solaria. Much more common are TV sets, electric ovens, computers and laptops: on average, virtually each German household possesses a laptop, a personal computer, and an electric oven.

The appliances presented 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 including further dummy variables for these and other appliances in our estimations, the associated electricity consumption is captured by incorporating household size dummies. As the number of small appliances, such as electric tooth brushes and chargers, tends to increase with the number of household members, it is plausible to assume growing coefficients for the household size dummies.

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. DALEN, LARSEN, 2015; HALVORSEN, LARSEN, 2001; HSIAO et al., 1995; 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. Otherwise, D_{ij} equals zero.

Our point of departure in estimating the determinants of electricity consumption y 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 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:

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

with $\alpha_l, \beta_j, \theta_k$, and ρ_{jm} being coefficients to be estimated and ε_i denoting 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 $l = 1, 2, ..., L$ household members, where L denotes household types with 4 and more members. While it is the stock of appliances that is responsible for a household's electricity consumption, as individuals cannot directly consume electricity (REISS, WHITE, 2005), household size dummies S_{il} are included to capture the residual electricity consumption that is due to all those appliances and end-use purposes that are not explicitly included in the specification by dummy or count variables.

Furthermore, the interaction term $\sum_{m=1}^{M} \rho_{jm}(C_{im} - \bar{C}_{jm})D_{ij}$ is an adjustment of electricity consumption for end use j that is due to deviations from the mean values for various 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} ($m = 1, 2, ..., M$), with $\bar{C}_{jm} := 1/H_j \sum_{k=1}^{n} C_{km}D_{kj}$ designating the mean value of these household characteristics for those of the H_j households that possess appliance j and n denoting the number of sample households.

Note that in Specification 1 an appliance type or an activity is either captured by dummy variable D_{ij} or by count variable N_{ik}, but not by both. For instance, washing, as well as dishwashing, is accounted for by counting the number of annual washing cycles to reflect usage intensity, but not by taking account of the availability of washing machines and dishwashers by including a dummy variable D_{ij}. 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 computer, θ_k provides the mean electricity consumption of an additional appliance. In contrast, parameter β_j reflects the mean electricity consumption with respect to end use j given that for all M household characteristics the variables 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 characteristic is relevant for end-use purpose j. Typically, though, all the individual household characteristics C_{im} 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 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. $\boldsymbol{\alpha}_\mathbf{x}(\tau)$ 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:

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

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 $F^{-1}_{\varepsilon_i}(\tau)$. In the special case that errors are independent and identically distributed, that is, if $F^{-1}_{\varepsilon_i}(\tau) = F^{-1}_{\varepsilon}(\tau)$ 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: $\alpha(\tau) + F^{-1}_{\varepsilon_i}(\tau)$. 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} with 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. For expositional 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 about 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 due to the lack of data. One reason is that respondents are uncertain about the prevalence of certain types of appliances, such as a heat 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. As expected (see Figure 1), 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 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 value, although the difference between the OLS estimates for these two household types is not statistically significant. These residual consumption values generally differ, because the number and size of the excluded appliances, as well as the intensity with which they are use, tend to increase with household size.

Due to the lack of data, we cannot control for the size, type, wattage and utilization of all appliances. As a consequence, the OLS coefficient estimates refer to an appliance of average size, efficiency and utilization. For example, the annual electricity

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

	OLS Regression		Median Regression	
		Robust		Robust
	Coeff.s	Std. Err.s	Coeff.s	Std. Err.s
Household Size				
2 Members	836.8**	(83.7)	743.4**	(74.8)
3 Members	1,351.4**	(130.0)	1,257.2**	(138.1)
4 and more members	1,312.7**	(159.5)	1,174.6**	(134.0)
Per week absent from home	-22.2**	(7.9)	-16.1**	(3.8)
Water heating	464.8**	(88.7)	476.2**	(69.0)
Air-conditioning	525.9	(473.5)	451.2	(393.7)
Per refrigerator	297.2**	(66.2)	394.5**	(57.1)
Per freezer	407.0**	(61.2)	447.1**	(47.5)
Electric oven	92.9	(112.7)	49.3	(86.7)
Per washing cycle	0.69	(0.36)	0.46	(0.28)
Per dish washing cycle	1.31**	(0.36)	1.50**	(0.36)
Per drying cycle	2.71**	(0.53)	2.73**	(0.50)
Per TV set	113.8**	(42.0)	129.6**	(38.2)
Aquarium or terrarium	757.6**	(157.4)	782.9**	(217.8)
Waterbed	519.2*	(224.8)	298.2	(235.3)
Sauna	290.9*	(146.2)	245.3	(152.2)
Solarium	416.5	(518.7)	376.6	(460.2)
Pond pump	374.4**	(102.9)	363.7**	(84.7)
Per computer	69.3*	(35.2)	117.7**	(30.2)
Per light bulb	10.3**	(2.7)	4.4	(2.6)
Per meal	0.41	(0.27)	0.22	(0.21)
Constant	658.5**	(160.0)	512.9**	(123.0)

Note: * denotes significance at the 5% level, ** at the 1% level. Number of observations used for estimation: 1,653.

consumption of a typical sample TV set amounts to 114 kWh, while that of a typical sample computer is about 70 kWh per year.

In the absence of data on the size, age, and efficiency label of appliances, differences in these characteristics may 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 consumption rates of appliances are higher among households with a large electricity consumption.

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

	Percentiles			F statistics for
	25th	50th	75th	Equality of Coefficients
	Coeff.s	Coeff.s	Coeff.s	of 25th and 75th Percentiles
Household Size				
2 Members	566.4**	743.4**	916.5**	9.19**
3 Members	986.9**	1,257.2**	1,611.5**	6.83**
4 and more members	976.0**	1,174.6**	1,241.1**	2.37**
Per week absent from home	-20.3**	-16.1**	-27.2**	0.45
Water heating	372.8**	476.2**	495.8**	1.08
Air-conditioning	540.2	451.2	513.6	0.00
Per refrigerator	253.0**	394.5**	318.3**	0.44
Per freezer	376.1**	447.1**	463.2**	0.94
Electric oven	62.8	49.3	93.3	0.03
Per washing cycle	0.85**	0.46	0.55	0.33
Per dish washing cycle	1.15**	1.50**	1.66**	0.94
Per drying cycle	2.73**	2.73**	3.11**	0.18
Per TV set	96.1**	129.6**	118.8**	0.19
Aquarium or terrarium	656.2**	782.9**	845.9*	0.41
Waterbed	296.5*	298.2	1040.3**	5.25*
Sauna	393.7**	245.3	337.7	0.06
Solarium	44.3	376.6	629.4*	0.37
Pond pump	375.5**	363.7**	385.4**	0.00
Per computer	57.8	117.7**	81.3*	0.19
Per light bulb	5.3*	4.4	15.9**	8.35**
Per meal	0.36*	0.22	0.29	0.03
Constant	376.7**	512.89**	980.8**	7.49**

Note: * 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 refrigerators of households from the 25th percentile, that is, 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. This seems plausible given that the efficiency level of appliances is an important factor in determining how much electricity a household consumes.

Turning to the heterogeneity in the results across quantiles, we find substantial differences across appliances and, most notably, the household size indicators (Table 4). In fact, the F tests on the equality of the coefficients for the 25th and the 75th 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 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 larger than 15 kWh. This finding may indicate potentials for energy savings when the lower consumption rate of households from the lower tail of the distribution reflect the usage of more efficient light bulbs.

The heterogeneity in the consumption rates 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 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 need about 80 kWh more electricity per annum. Similar pictures can be drawn for other appliances.

5 End-Use Shares

Using the quantile regression estimates reported in Table 4, for households belonging to different parts of the consumption distribution, we now calculate the shares of electricity consumption that can be attributed to diverse end-use purposes, such as cooling and lighting. Following 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 an appliance type in quantile τ, and the corresponding estimate $\widehat{\beta}_j(\tau)$ of the consumption rate for quantile τ, and multiply both 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

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

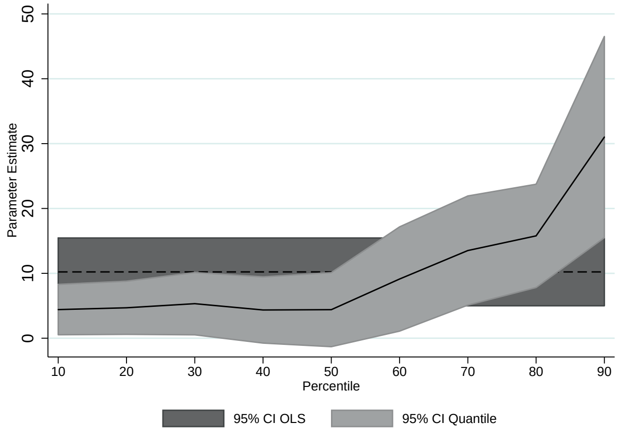
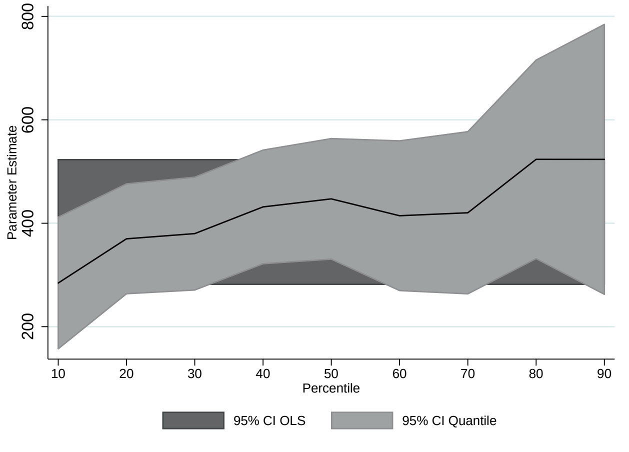


Figure 3: Comparison of OLS and Quantile Regression Results for the Electricity Consumption Rates of Freezers



predicted consumption of appliance j therefore reads: $\hat{y}_j(\tau) = \widehat{\beta}_j(\tau)\bar{D}_j(\tau)$.

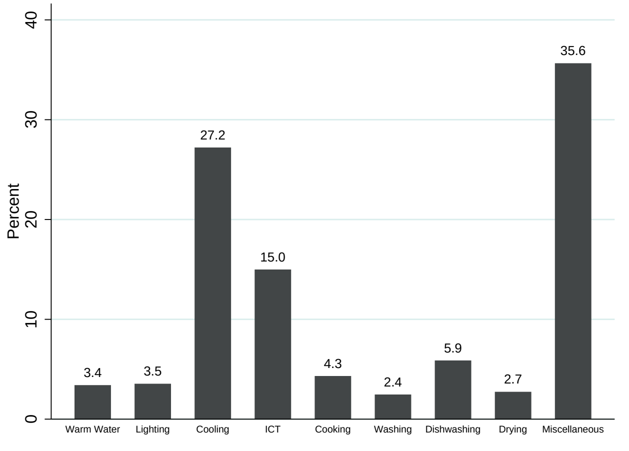
The predicted end-use share of appliance j for quantile τ is then given by $\hat{s}_j(\tau) := \frac{\hat{y}_j(\tau)}{y(\tau)}$, where $y(\tau)$ denotes total electricity consumption of all households of quantile τ. In a similar vein, for appliances for which their number N_{ik} is employed as a regressor, the end-use share is given by $\hat{s}_k(\tau) := \frac{\hat{y}_k(\tau)}{y(\tau)}$, where $\hat{y}_k(\tau) = \widehat{\theta}_k(\tau)\bar{N}_k(\tau)$ and $\widehat{\theta}_k(\tau)$ denotes the corresponding 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 in quantile τ.

The results of these exercises are presented in Figures 4 to 6. Note that heating purposes do not appear in these figures, as households heating solely 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, heating solely 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 3.4% in the total electricity consumption of those households that are located in the middle of the consumption distribution (Figure 4). By contrast, with a share of about 27%, 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 4.4% of our sample households employ air-conditioning devices (Table 2). Another – increasingly important – purpose of electricity demand is for information and communication (ICT), which encompasses here the consumption of personal computers, laptops, and television sets. The respective share amounted to about 15% for the median consumer in 2013.

With almost 36%, 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 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, such as waterbed, sauna, pond pump, swimming pool, solarium, etc. Recall that the dummies for household size capture the residual electricity consumption that is due to all those appliances and end-use purposes that are not explicitly included in Specification 1.

Figure 4: Shares of various End-Use Purposes for the 50th Percentile in German Residential Electricity Consumption in 2013.



As becomes evident from our quantile regression results and the following figures for households originating from the 25th and 75th percentiles in the residential electricity consumption distribution, the importance of consumption purposes varies across household types. For instance, for households belonging to the 75th percentile of electricity consumption (Figure 6), cooling and cooking purposes are of a notably smaller significance than in households of the 25th percentile, 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 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.

Figure 5: Shares of various End-Use Purposes for the 25th Percentile in German Residential Electricity Consumption in 2013.

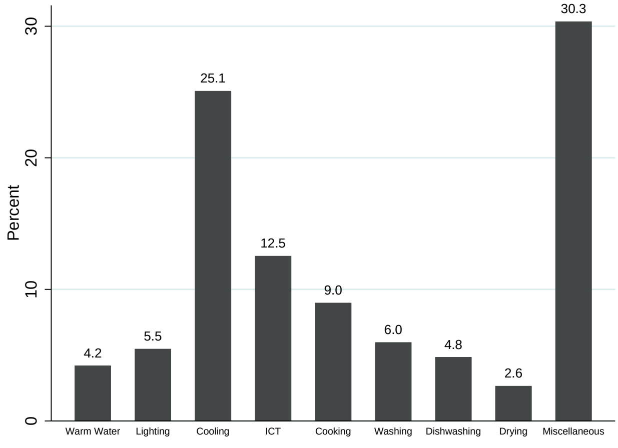
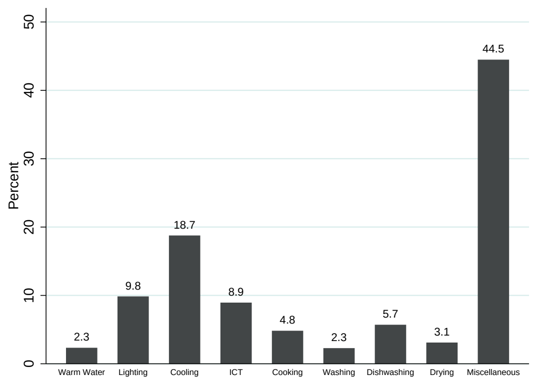


Figure 6: Shares of diverse End-Use Purposes for the 75th Percentile in German Residential Electricity Consumption in 2013.



6 Summary and Conclusions

This paper has employed the conditional demand approach to estimate the contribution of common household appliances to electricity demand from a sample of about

2,100 German households. Moving beyond the standard focus of estimating mean effects via OLS, 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 consumption 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 either dummy or count variables for each appliance type and estimating their influence on the basis of quantile methods 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	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 > €4,700	0.106	0.102
Aged between 18 and 34	0.056	0.193
Aged between 35 and 64	0.588	0.526
Aged 65 and above	0.356	0.281
Unemployed	0.432	0.352
Woman	0.309	0.352
High school degree	0.255	0.316
Children in household	0.171	0.287

Source: DESTATIS (2014)

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