RUHR
ECONOMIC PAPERS

Manuel Frondel
Gerhard Kussel

Switching on Electricity Demand Response: Evidence for German Households

#763

Imprint

Ruhr Economic Papers

Published by

RWI – Leibniz-Institut für Wirtschaftsforschung
Hohenzollernstr. 1-3, 45128 Essen, Germany

Ruhr-Universität Bochum (RUB), Department of Economics
Universitätsstr. 150, 44801 Bochum, Germany

Technische Universität Dortmund, Department of Economic and Social Sciences
Vogelpothsweg 87, 44227 Dortmund, Germany

Universität Duisburg-Essen, Department of Economics
Universitätsstr. 12, 45117 Essen, Germany

Editors

Editorial Office

Ruhr Economic Papers #763

Responsible Editor: Manuel Frondel

ISSN 1864-4872 (online) – ISBN 978-3-86788-890-5

Ruhr Economic Papers #763

Manuel Frondel and Gerhard Kussel

Switching on Electricity Demand Response: Evidence for German Households

Bibliografische Informationen der Deutschen Nationalbibliothek

The Deutsche Nationalbibliothek lists this publication in the Deutsche Nationalbibliografie; detailed bibliographic data are available on the Internet at http://dnb.dnb.de

RWI is funded by the Federal Government and the federal state of North Rhine-Westphalia.

http://dx.doi.org/10.4419/86788890
ISSN 1864-4872 (online)
ISBN 978-3-86788-890-5

Manuel Frondel and Gerhard Kussel[1]

Switching on Electricity Demand Response: Evidence for German Households

Abstract

Empirical evidence on households' awareness of electricity prices and potentially divergent demand responses to price changes conditional on price knowledge is scant. Using panel data originating from Germany's Residential Energy Consumption Survey (GRECS), we fill this void by employing an instrumental-variable (IV) approach to cope with the endogeneity of the consumers' tariff choice. By additionally exploiting information on the households' knowledge about power prices, we combine the IV approach with an Endogenous Switching Regression Model to estimate price elasticities for two groups of households, finding that only those households that are informed about prices are sensitive to price changes, whereas the electricity demand of uninformed households is entirely price-inelastic. Based on these results, to curb the electricity consumption of the household sector and its environmental impact, we suggest implementing low-cost information measures on a large scale, such as improving the transparency of tariffs, thereby increasing the saliency of prices.

JEL Classification: Q41, D12

Keywords: Price elasticity; switching regression model; information

August 2018

1 Both RWI and RUB. - We are grateful to the Federal Ministry of Eduction and Research (BMBF) for financial support under the program "Economics of Climate Change", grants 01LA1113A and 01LA1113B, and 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". We appreciate the valuable comments and suggestions by Colin Vance and four anonymous reviewers, as well as participants of the research seminar of the economics department of Giessen University, the annual conference of Verein für Socialpolitik, Augsburg, and summer school participants of the Cologne International Energy Summer in Energy and Environmental Economics.– All correspondence to: Manuel Frondel, RWI, Hohenzollernstr. 1-3, 45128 Essen, Germany, e-mail: manuel.frondel@rwi-essen.de

1 Introduction

Recent evidence from experimental economics indicates that the sluggishness of consumers' response to price changes may be due to insufficient price knowledge (Jessoe and Rapson, 2014). Ignoring this fact in estimating demand responses may result in elasticity estimates that incorrectly reflect the responses of consumers who are aware of prices. Further obstacles to consistently estimating demand elasticities emerge from the prevalence of tariffs that include a fixed fee, as this would lead to endogeneity bias (Taylor et al., 2004). This kind of tariff is standard in numerous retail markets, such as telecommunications, water, natural gas, as well as electricity markets. Endogeneity issues are all the more relevant if consumers are free to choose from a broad range of tariffs. Such is the circumstance in Germany since the liberalization of the electricity markets in the European Union (EU) in 1998.

Employing an instrumental-variable (IV) approach to cope with the likely endogenous tariff choice, this article estimates the households' response to power price changes based on panel data originating from Germany's Residential Energy Consumption Survey (GRECS) for the years 2011 and 2012, thereby adding to the growing literature on the price responsiveness of residential electricity demand by investigating the role that information plays in influencing customer response. While being a standard method for dealing with the endogeneity of an explanatory variable, IV approaches are less frequently applied with respect to estimating electricity demand responses. A rare exception is the study by Alberini and Fillipini (2011), who explicitly instrument for price to remedy the measurement error in their price variable.

As instrument for the endogenous price variable, we use the composite of grid and licence fees. Given that these fees are part of the end-use price and account for about 26% of average household prices, our instrument is clearly correlated with the endogenous price variable. Moreover, these fees are set by grid operators and are fixed at the regional level, so that it is highly warranted to assume that this price component is exogenous to consumers and, hence, does not affect consumers' tariff choice. Using components of a tariff as a source of exogenous variation, such as grid and licence fees, we follow a fairly common identification strategy in the empirical literature (e. g. Ito (2014)). A distinguishing feature of our analysis is that we exploit sample information on the households' knowledge about power prices. On this basis, we combine the IV approach with an Endogenous Switching Regression Model to estimate price elasticities for two groups of households, finding that only those households that are informed about prices are sensitive to price changes, whereas the electricity demand of uninformed households is entirely price-inelastic.

These results suggest increasing the transparency of tariffs and cast doubt on both the efficacy and the welfare effects of Germany's eco-tax, which was introduced in 1999 to curb the greenhouse gas emissions from electricity consumption. This tax contributed to the doubling of the electricity prices for households since the beginning of the new millennium (BDEW, 2017:29), when prices reached their minimum after the liberalization of the electricity market in 1998. A key consequence of this liberalization for households was the opportunity to freely choose their electricity provider. The improved competition was not sufficient, however, to moderate retail prices (Ros, 2017), which primarily increased due to the introduction of new taxes and levies (BNetzA, 2017). Currently, taxes and levies account for slightly more than half of the power prices for German households (BDEW, 2017:30).

Another key reason for rising power prices was the introduction of a feed-in tariff scheme to support renewable energy technologies in 2000 (Andor et al., 2017a). While this support scheme was very effective in increasing the share of green electricity in gross production, from less than 7% in 2000 to around 36% in 2017 (BDEW, 2018), the resulting burden for consumers particularly mounted in recent years, above all due to the exploding expansion of photovoltaic capacities (Frondel et al., 2015). As a consequence, the levy with which electricity consumers have to finance the support for green electricity more than quadrupled between 2009 and 2018, increasing from 1.31 to 6.79 cents per kWh. Today, German households have to bear electricity prices that are – in terms of purchasing power standards – the highest in the EU (Eurostat, 2017). Yet, whether the doubling of average household electricity prices since 2000 has induced substantial reductions in electricity demand critically depends on households' responsiveness to price changes.

Based on our key empirical result that only price-conscious consumers exhibit a price-elastic demand and given that Germany's electricity production still largely rests on coal and natural gas, an important policy implication suggests itself: to dampen the electricity consumption of the household sector and its environmental impact, low-cost information measures, such as increasing the transparency of tariffs, should be implemented on a large scale in order to increase the saliency of prices.

The subsequent section provides a brief review of the literature on the residential demand for electricity. Section 3 concisely summarizes our database, followed by the presentation of the estimation results in Sections 4 and 5. Based on our empirical results, Section 6 presents some policy recommendations. The last section closes with a summary and conclusions.

2 Findings from the Literature

The received empirical literature suggests that price knowledge may substantially alter the demand for goods and services. For instance, analyzing the effect of detailed price information presented on water bills, Gaudin (2006) finds that households that are aware of price levels are considerably more sensitive to price changes than price-ignorant households. In a similar vein, examining the effect of price knowledge for various utility services, Carter and Milon (2005) also conclude that informed households are more responsive to price changes than those without any clue about prices.

For electricity markets, though, empirical evidence on the impact of price information is scarce and primarily available for markets with real-time or time-of-use pricing schemes. Investigating the impact of price information on demand patterns under time-of-use pricing, recent studies, such as Harding and Lamarche (2016) and Pon (2017), detect a large price response due to intra-day demand shifting. With respect to real-time pricing, Martin and Rivers (2018) find evidence that households respond to this information in part by forming habits, rather than adjusting their load-shifting behavior, resulting in a reduction in average electricity consumption of about 3%, an effect that is roughly constant across hours of the day. This result is based on a large-scale field deployment in which close to 7,000 households were provided with real-time feedback on electricity consumption and prices. Exploring the implications of real-time pricing for Swedish households, Vesterberg and Krishnamurthy (2016) also estimate small cost savings from shifting load up to five hours ahead. These results indicate weak incentives for households and retailers to adopt dynamic pricing of electricity.

There are also studies that investigate the effect of information on usage, rather than prices, on electricity demand. Based on experimental data from Japan, Matsukawa (2004), for instance, measures the effects of usage information received from a monitoring device on residential demand for electricity, the results indicating that this information contributed to energy conservation. Another example is the randomized control trial used by Jessoe and Rapson (2014) to test the effect of high-frequency information about residential electricity usage on the price elasticity of demand. These authors provide experimental evidence that informed households are more responsive to temporary price increases, concluding that inefficiencies due to imperfect information about product attributes can be overcome by providing easy-to-grasp information on a low-cost basis.

Our empirical analysis adds to this line of inquiry by providing evidence on the effect of price knowledge on electricity consumption levels in retail markets without real-time or time-of-use pricing schemes. Although the demand for electricity has been investigated by economists ever since its discovery, no broad consensus has been reached about the size of the response of residential electricity demand to changing power prices. In fact, price elasticity estimates cover a large range, stretching from 0, that is, an entirely price-inelastic demand, to a highly elastic response as indicated by an elasticity estimate of about -2.5 (Alberini and Fillipini, 2011; Fell et al., 2014; Labandeira et al., 2006; Reiss and White, 2005; Schulte and Heindl, 2017; Shin, 1985; Taylor, 1975).

A key reason for these huge discrepancies is the specification of the price variable (Espey et al., 2004). While a central assumption in economic theory is that consumers optimize with respect to marginal prices (Ito, 2014:537), recent empirical findings suggest that consumers tend to react to alternative price measures. Ito (2014), for instance, finds strong evidence that households respond to average prices, rather than (expected) marginal prices. By analyzing the price measure issue as well, Borenstein (2009) comes to similar conclusions, claiming that, as a consequence of the non-linearity of tariffs, consumers do not respond to marginal prices due to the lack of precise price knowledge.

While such results suggest the use of average prices in estimating demand responses, this approach can lead to biased results if tariffs entail a fixed fee. While Baker et al. (1989) claim that the bias due to fixed fees is small, Taylor et al. (2004) argue that large magnitudes of price elasticity estimates, as well as good model fits, are just statistical artifacts of the usage of the average price as price measure, with the average price ap being defined as follows:

$$ap := \frac{q \cdot mp + f}{q}, \tag{1}$$

where q denotes consumption, mp designates the marginal price, and f the fixed fee.

In fact, it is straightforward to demonstrate that $\frac{\partial \ln q}{\partial \ln ap}$, the price elasticity of demand, approaches -1 if the average price ap is much larger than the marginal price mp: $ap >> mp$. Rearranging definition (1) yields $q = f/(ap - mp)$ and, hence, $\frac{\partial q}{\partial ap} = -f/(ap - mp)^2 = -q/(ap - mp)$. This derivative constitutes the demand elasticity with respect to the average price ap:

$$\frac{\partial \ln q}{\partial \ln ap} = \frac{ap}{q} \cdot \frac{\partial q}{\partial ap} = -\frac{ap}{q} \cdot \frac{q}{ap - mp} = -1 - \frac{mp}{ap - mp}, \tag{2}$$

where the last term approaches -1 for $ap >> mp$.

In sum, irrespective of the service under scrutiny, we arrive at the general conclusion that in case of tariffs that include a fixed fee, using average prices for estimating price elasticities may lead to the overestimation of demand responses. This issue is highly relevant for our analysis, as the dominating pricing model in Germany's retail market for electricity includes two components: a fixed fee, whose annual amount varies between €0 and €1,000 for our sample households, and a constant marginal price per kilowatt-hour (kWh). Note also that the average price is an endogenous measure, as, by definition, it is a function of electricity consumption, the dependent variable of our analysis.

As these arguments cast doubt on the usage of average prices when estimating price responses, in our empirical approach, we employ marginal prices as the sole price measure. This appears to be all the more warranted, as it is more easy for German households to find the constant marginal price per kWh on their bill than to calculate the average price per kWh by dividing total payments by total consumption. If at all, therefore, German households are aware of marginal prices, rather than the average cost per kWh. This strongly contrasts with countries such as the U. S., in which nonlinear block tariffs dominate the retail electricity markets and, hence, the information cost of understanding the marginal price of electricity is likely to be substantial (Ito, 2014:560). By contrast, block tariffs are entirely absent in Germany.

3 Data

Our analysis draws on a rich panel data set originating from a retrospective survey among about 8,500 households conducted in 2014 as part of the German Residential

Energy Consumption Survey (GRECS), a survey that has been regularly commissioned by the Federal Ministry of Economics and Energy (BMWi) for more than a decade (RWI and forsa, 2018). In addition to information on electricity consumption and cost, which households report from their electricity bills for the years 2011 and 2012, this survey provides for detailed information on socio-economic and other household characteristics, such as household size and household net income, age and education of the household head, and ownership of the household's residence.[1]

All this information is self-reported under close guidance of a state-of-the art survey tool that provides visual assistance to the respondents, particularly with respect to electricity bills. For example, after being asked to indicate their electricity provider, respondents received a picture of the respective billing sheet, with the position of the required information being highlighted on the billing sheet – for more information, see RWI and forsa (2015). Data on grid and license fees at the 5-digit postcode level for the years 2011 and 2012 were purchased from *ene't*, a professional provider of energy-related data. Information on whether a household resides in a rural or urban area, available from the Federal Statistical Office (Destatis 2015), completes our database.

The billing information includes marginal prices mp per kWh, monthly fixed fees f, total electricity expenditures, and consumption levels q.[2] As indicated by the standard deviation of 0.03 Euro per kWh reported in Table 1, price variation amounts to 15% of the average marginal price of 0.20 Euro per kWh and originates from the fact that consumers can easily change their provider and can choose among a large variety of providers offering attractive tariffs for new customers. From the billing data, we have extracted the annual electricity consumption and prices. In the frequent case that a bill does not cover the entire calender year, we have extrapolated the annual consumption

[1] The time lag between the survey year 2014 and the years 2011 and 2012, for which billing information is gathered, is due to the fact that bills are available only with a time lag of at least one year, as this is the usual billing period. If several bills are available that at least partly cover either of the years 2011 and 2012, we have computed the marginal price as weighted mean, taking billing days per calendar year as weights.

[2] Households with night storage heating systems, which represent a small minority of less than 3% of the German household population, have been excluded from our sample, as their electricity consumption is substantially above average and they enjoy a separate low tariff for heating purposes.

on the basis of the mean consumption per day for the period for which information is available.

Table 1: **Descriptive Statistics for the Estimation Sample**

	Variable Definition	Mean	Std. Dev.
q	Household electricity consumption in kWh	3,668	2,090
mp	Marginal electricity price in €/kWh	0.20	0.03
z	Sum of grid and license fees in €/kWh	0.07	0.01
f	Fixed fees in €/year	175.2	230.8
Household income	Net household income in 1,000 €	3,039	1,412
Household size	Household size	2.36	1.12
Household size = 1	Dummy: 1 if household size = 1	0.20	–
Household size = 2	Dummy: 1 if household size = 2	0.46	–
Household size = 3	Dummy: 1 if household size = 3	0.17	–
Household size = 4	Dummy: 1 if household size = 4	0.13	–
Household size > 4	Dummy: 1 if household size > 4	0.04	–
Age	Age of respondent	53.67	12.91
Female	Dummy: 1 if respondent is female	0.31	–
College degree	Dummy: 1 if household head has a college degree	0.44	–
Home ownership	Dummy: 1 if household resides in own propriety	0.67	–
Rural area	Dummy: 1 if household resides in a rural area	0.20	–
East Germany	Dummy: 1 if household resides in East Germany	0.16	–
Year 2012	Dummy: 1 if electricity bill originates from 2012	0.52	–
Supplier change	Dummy: 1 if household changed its supplier	0.31	–
	in the years 2011-2013 prior to the survey	–	–

Note: Number of observations: 6,528; number of households: 3,550. Income was provided in categories, from which a continuous variable has been derived by using class middles as the reference point.

According to our experience with conducting the GRECS, typically about two thirds of all survey households are unable to provide reliable information on their electricity bills, mostly because bills for former years are unavailable. Moreover, we have skipped observations from households that provided information for less than 30 billing days. Nonetheless, our analysis benefits from a rich database: Overall, our estimation sample consists of 3,550 households and a total of 6,528 observations (Table 1), implying a mean number of 1.84 observations per household: for 2,978 households, information on both years 2011 and 2012 is available (5,956 observations), 191 households merely provided data for 2011 and 381 observations solely refer to 2012.

Before reporting their billing information, the respondents were requested to gauge the marginal price per kWh they had to pay for 2012. By comparing each household's estimate with the price that was actually paid, we have been able to construct an indicator for a household's price knowledge: If a household's ex-ante estimate deviates by less than $\pm$ 20% from the actual marginal price, this indicator equals 1 and is set to 0 otherwise. According to this definition, 63% of our sample households have at least a minimum impression of marginal prices. Alternative bandwidths based on deviations of $\pm$ 10% and $\pm$ 15% have also been employed for the definition of price knowledge, leaving our estimation results largely unaltered.

For the identification of the switching regression model, described in detail in Section 5, non-linearity of the specification is sufficient (Cameron and Trivedi, 2009). For a more robust identification, it is typically recommended to impose an exclusion restriction, requiring at least one variable that in our example determines the respondents' price knowledge, yet not their electricity consumption level. To this end, we exploit the information on whether a household changed its electricity supplier during the three years prior to the survey, captured by the binary variable supplier change (Table 1). 31% of our sample households changed their electricity supplier during the years 2011-2013 prior to the survey. It seems plausible that households searching for a new supplier gather information on tariffs and prices and, hence, become familiar with power prices. This assumption is confirmed by the first-stage results of the Switching Regression Model, which indicate a positive correlation between price knowledge and supplier change (Table 3). Of course, this positive correlation may also reflect that price-informed households are more likely to change the supplier. Either way, the exclusion restriction that the variable supplier change is assumed to not emerge in the second-stage regression of the switching regression model allows for a more robust identification by reducing potential multi-collinearity problems in the second stage.

With 3,668 kWh, our sample households' average electricity consumption per annum roughly matches the annual consumption of a typical German household, which amounts to about 3,500 kWh according to BNetzA (2017). In addition, with € 3,039 per month, the mean net income of our sample households is very close to the amount of € 3,069 that is reported as average income for German households in 2012 by the German Federal Statistical Office (Destatis, 2015).

Unlike electricity consumption and net income, though, there are substantial differences between our sample and the German population with respect to other variables. For example, with 67%, the share of homeowners in our sample is far higher than the share of almost 46% that is published by the German Federal Statistical Office (Destatis, 2014). A key reason for this discrepancy is that in responding to the survey questions on electricity cost and consumption for 2012, the share of tenants who can resort to information from electricity bills is lower than the respective share of homeowners, not least due to the fact that tenants move more frequently than homeowners.

As instrument z for the likely endogenous price variable, we employ the composite of local grid and license fees, which are region-specific and account for about one quarter of the average consumer price (BDEW, 2017:30). While taxes and levies, such as the surcharge for the support of renewable technologies, are the same for all household consumers, grid and license fees significantly differ across regions. In fact, grid fees are the highest in those federal states with the strongest expansion of wind power capacities, most notably in North and East Germany, as the connection of these additional capacities necessitates the augmentation and enhancement of the existing power grids, as well as the installation of new power lines. As all households of the same grid area have to pay the same grid and license fees irrespective of which tariff and supplier a household chooses, it is highly warranted to assume that this price component is exogenous to consumers and that, in formal terms, our instrument z is not correlated with the error term ε of any regression specification. In short, both identification assumptions for valid instruments should hold: (1) $Cov(mp, z) \neq 0$ and (2) $Cov(\varepsilon, z) = 0$.

4 Panel Estimation Results

To provide for a reference case for the IV estimates, we first use standard panel estimation methods to estimate the double-log specification that is typically employed when the estimation of elasticities is at issue:

$$\ln(q_{it}) = \alpha + \alpha_{mp} \cdot \ln(mp_{it}) + \boldsymbol{\alpha}^T \cdot \mathbf{x}_{it} + \gamma_i + \varepsilon_{it}, \tag{3}$$

where $\ln(q_{it})$ denotes the natural logarithm of the annual electricity consumption q_{it} of household i at time t, mp stands for the marginal price, $\mathbf{x}$ is a vector of household characteristics, γ_i denotes the household-specific effect and ε designates the error term.

The random-effects estimation results for structural Equation 3 yield a totally inelastic demand response to marginal prices (Table 2): With a standard error of 0.033, the coefficient estimate of 0.036 is not significantly different from zero in statistical terms. A similar finding of a negligible demand response to marginal prices results from the fixed-effects estimation of Equation 3, with the results being reported in Table A.1 of the appendix. In what follows, we prefer reporting random-effects estimates, rather than fixed-effects results, as with respect to our IV approach fixed-effects estimations suffer from weak identification problems, because time- and household fixed effects absorb much of the variation in our instrument. This results in an implausibly large price effect, as well as a large standard error (see Table A.1).

When employing marginal prices for estimating electricity demand responses, one must recognize that prices are likely to be endogenous, as rational customers tend to select contracts that minimize their electricity costs. In fact, the average price of those 49% of our sample households that reported to have changed the electricity provider at least once in their life amounts to 25.35 cents/kWh for the years 2011 and 2012, whereas for those that have never changed the supplier the average price amounts to 26.05 cents/kWh, implying a slightly, but significantly higher average price for those sticking with their supplier (t = 8.71). In contrast, in former monopolistic markets, which

Table 2: **Random-Effects Estimation Results for Logged Annual Electricity Consumption**

Dependent Variable:	Standard Random Effects $\ln q$		Random-Effects IV Estimation First Stage $\ln mp$		Random-Effects IV Estimation Second Stage $\ln q$	
	Coeff. s	Std. Errors	Coeff. s	Std. Errors	Coeff. s	Std. Errors
$\ln z$	–	–	0.171**	(0.020)	–	–
$\ln mp$	0.036	(0.033)	–	–	–	–
$\widehat{\ln mp}$	–	–	–	–	-0.516*	(0.259)
ln household income	0.145**	(0.017)	-0.020**	(0.005)	0.109**	(0.017)
Household size = 2	0.351**	(0.021)	-0.006	(0.006)	0.395**	(0.019)
Household size = 3	0.529**	(0.024)	-0.009	(0.007)	0.628**	(0.023)
Household size = 4	0.635**	(0.026)	-0.011	(0.008)	0.724**	(0.025)
Household size > 4	0.800**	(0.037)	0.005	(0.011)	0.910**	(0.035)
Age	0.005**	(0.001)	-0.001*	(0.000)	0.006**	(0.001)
Female	-0.035*	(0.014)	-0.016**	(0.005)	-0.041**	(0.015)
College degree	-0.036**	(0.014)	0.006	(0.005)	-0.026	(0.014)
Home ownership	0.207**	(0.016)	-0.014*	(0.006)	0.182**	(0.016)
Rural area	0.104**	(0.016)	0.027**	(0.006)	0.109**	(0.017)
East Germany	-0.101**	(0.018)	0.012	(0.007)	-0.089**	(0.020)
Year 2012	-0.004	(0.003)	0.036**	(0.002)	0.019	(0.012)
# observations:	6,528		6,528		6,528	

Note: Standard errors are clustered at the post code level; * and ** denote statistical significance at the 5% and 1% level, respectively. Employed number of observations per household: 1,84. Kleibergen-Paap F statistic: 104.37

prevailed before the liberalization of Germany's electricity market in 1998, households had no opportunity at all to choose their provider and tariff, but were stuck with their local electricity provider, and, thus, electricity prices were clearly exogenous to households.

Yet, the price structure of the former monopolistic era, including a monthly fixed fee, as well as a constant marginal price that is independent of consumption levels, still remains the dominant tariff today, whereas alternatives, such as package and flat-rate tariffs, are rarely offered. But as changing both suppliers and tariffs is now a common phenomenon, a simultaneity problem may arise: while, on the one hand, consumption levels tend to be affected by prices, on the other hand, households' tariff selection may depend on consumption levels.

To cope with this simultaneity problem, we pursue a panel IV approach and employ the composite of the local grid and license fees as instrumental variable z for the likely endogenous marginal price, noting that a correlation coefficient of 0.23 reflects the expected positive correlation between z and marginal prices mp. This positive correlation can also be observed from the OLS estimation results of the first stage of the IV regression that is given by Equation 4:

$$\ln(mp_{it}) = \beta + \beta_z \cdot \ln(z_{it}) + \boldsymbol{\beta}^T \cdot \mathbf{x}_{it} + \nu_{it}, \tag{4}$$

where the marginal price mp is regressed on our instrumental variable z and the vector $\mathbf{x}$ of household characteristics, while ν designates another error term. Given that the estimate of coefficient β_z, reported in Table 2, is positive and statistically significant at the 1% significance level, there is statistical evidence that the first assumption for valid instruments holds: $Cov(mp, z) \neq 0$.

At the second stage of the IV approach, instead of employing observed marginal prices mp, structural Equation 3 is estimated using the predictions $\widehat{\ln mp}$ that are obtained from estimating first-stage Equation 4. The results of the second-stage regression indicate that, approximately, a 10% increase in marginal electricity prices is associated with a decrease in electricity use of -5.2% (Table 2). This estimate falls on the lower end of the international evidence on electricity price elasticities (see Section 2). Yet, as elasticity estimates are hardly comparable across countries due to country-specific heterogeneity, it is reasonable to compare our estimate with those of former German studies. While empirical evidence for Germany is rare, our price elasticity estimate is in line with Schulte and Heindl (2017). These authors find a quite similar own-price elasticity of -0.43 for German residential electricity consumption (1993-2008), using cross-sectional data originating from Germany's Income and Expenditure Survey, which is conducted at 5-year intervals.

Much less elastic is the household response with respect to income: An increase in household net income by 10% induces an increase in electricity consumption of about 1%. While appearing low at first glance, this income elasticity estimate may be the result of two opposing effects: on the one hand, as is characteristic for normal goods, the demand for electrical services increases with income. On the other hand, high household incomes allow for the opportunity to invest in new, more efficient appliances that may dampen the electricity demand (Spees and Lave, 2007).

The outcomes of the remaining variables are largely in accord with our expectations: While homeowners, elder people, and those living in rural areas have a higher electricity consumption than other households, it is a well-known fact that, on average, households residing in East Germany consume less electricity (RWI and forsa, 2018), as well as households with a female head (Table 2). Not surprisingly, household size is an important driver of electricity consumption. The electricity use of a 3-person household, for example, is 87% = 100[exp(0.628)-1] higher than that of a 1-person household.

An important drawback of IV estimates is that their standard errors are typically larger than those of the respective OLS estimates (Bauer et al., 2009:327). In fact, if a variable that is deemed to be endogenous is instead exogenous, the IV estimator will be less efficient than the OLS estimator, while both estimators will be consistent. If an instrument is only weakly correlated with an endogenous regressor, the loss of precision of IV estimators may be severe. Even worse is that with weak instruments, IV estimates are inconsistent and biased in the same direction as OLS estimates (Chao and Swanson, 2005). Most disconcertingly, as is pointed out by Bound et al. (1993, 1995), when the instruments are only weakly correlated with the endogenous variables, the cure in the form of the IV approach can be worse than the disease resulting from biased and inconsistent OLS estimates. Given these potential problems, it is reasonable to perform an endogeneity test that examines whether a potentially endogenous variable is in fact exogenous.

To this end, following the essential idea of the Durbin-Wu-Hausman test for endogeneity (Hausman, 1978), we test whether the error term ν of Equation 4 is correlated with the error term ε of structural Equation 3. Although neither ε nor ν can be observed, one can employ the residuals of the first- and second-stage regressions and test whether they are correlated. Alternatively, one can plug the residual $\hat{v}$ as an additional regressor into structural Equation 3 and test its statistical significance (Davidson and MacKinnon, 1989). Pursuing this approach yields a coefficient estimate – not reported here – that is significant at the 1% significance level, providing strong evidence for the endogeneity of marginal prices.

While this outcome suggests the application of the IV approach, its validity depends on the strength of our instrument. Given that the standard errors are not identically distributed, nor independent, as observations are clustered at the household level, the weakness of instruments is tested using a Wald test (Kleibergen and Paap, 2006). With an F statistic of F = 104.37 for the coefficient β_z of the first-stage regression (Equation 4), which is well above the threshold of 16.38 given by Stock and Yogo (2005), we can reject the null hypothesis of weak identification.

5 The Effect of Price Knowledge

To explore the potential heterogeneity in price responses with respect to price awareness, we exploit sample information on the households' knowledge about power prices and estimate price responses for two groups of households: those that were able to gauge their individual electricity price with less than 20% deviation (Group 1: price knowledge = 1) and those that were not (Group 0: price knowledge = 0). This information is used in two distinct ways: On the one hand, we separately estimate structural Equation 3 for each of these groups and, on the other hand, we employ an Endogenous Switching Regression Model (Maddala, 1983) to account for the potential nonrandomness of a household being in either of these two groups. It bears noting that, either way, we cope with the endogeneity of the marginal price in the same manner as in the previous section: by replacing marginal prices with the IV predictions originating from estimating the first stage Equation 4 of our IV approach.

The Endogenous Switching Regression Model consists of two stages, with the first stage modeling the selection into either group: Group 1 (price knowledge = 1) and Group 0 (price knowledge = 0). In our example, this selection is modeled by the following binary variable:

$$\text{price knowledge} = \begin{cases} 1 & \text{if } \boldsymbol{\gamma} \cdot \mathbf{w}_i \geq u_i, \\ 0 & \text{otherwise,} \end{cases} \tag{5}$$

where $\mathbf{w}_i$ encompasses those household characteristics that may affect whether a household is informed about prices, γ is the corresponding parameter vector, and the error term u is assumed to be correlated with both error terms η_1 and η_0 emerging from the following structural Equations 6 and 7, as there may be unobservable factors that are relevant for both the selection into either group and the consumption level.

Conditional on a household's price awareness, the households' response to price changes is described by two equations that are analogous to structural Equation 3:

$$\ln(q_{1it}) = \alpha_1 + \alpha_{1p} \cdot \ln(p_{it}) + \boldsymbol{\alpha}_1 \cdot \mathbf{x}_{1it} - \sigma_{1u} \cdot \text{IVM}_{1i} + \eta_{1it} \text{ if price knowledge = 1,} \tag{6}$$

$$\ln(q_{0it}) = \alpha_0 + \alpha_{0p} \cdot \ln(p_{it}) + \boldsymbol{\alpha}_0 \cdot \mathbf{x}_{0it} + \sigma_{0u} \cdot \text{IVM}_{0i} + \eta_{0it} \text{ if price knowledge = 0,} \tag{7}$$

where η_1 and η_0 are error terms with zero conditional mean and

$$\text{IVM}_{1i} := \frac{\phi(\boldsymbol{\gamma}^T \cdot \mathbf{w}_i)}{\Phi(\boldsymbol{\gamma}^T \cdot \mathbf{w}_i)}, \qquad \text{IVM}_{0i} := \frac{\phi(\boldsymbol{\gamma}^T \cdot \mathbf{w}_i)}{1 - \Phi(\boldsymbol{\gamma}^T \cdot \mathbf{w}_i)} \tag{8}$$

represent the two variants of the inverse Mills ratios, with $\phi(.)$ and $\Phi(.)$ denoting the density and cumulative density function of the standard normal distribution, respectively.

When appended as extra regressors in the second-stage estimation, the inverse Mills ratios are controls for potential biases arising from sample selectivity. Selectivity is possible due to unobservable characteristics, such as carelessness about both electricity consumption and bills, that may affect both consumption levels and price awareness. If the estimates of the coefficients σ_{0u} and σ_{1u} of the inverse Mills ratios IVM_0 and IVM_1 are statistically significant, this is an indication of sample selectivity. To investigate this issue, in line with e. g. Andor et al. (2017b), we apply a two-stage procedure for the estimation of the Switching Regression Model, where for the second stage the predicted values $\widehat{\text{IVM}}_0$ and $\widehat{\text{IVM}}_1$ are employed as estimates for the inverse Mills ratios IVM_0 and IVM_1, with the predictions $\widehat{\text{IVM}}_0$ and $\widehat{\text{IVM}}_1$ being based on the estimates $\widehat{\gamma}$ of the first-stage probit estimation of price knowledge (see Equation 5).

Table 3: **Two-Stage Switching Regression Results based on Random-Effects Estimations, with the First Stage Estimates Resulting from Probit Estimations.**

	First Stage		Second Stage			
			Price knowledge = 1		Price knowledge = 0	
Dependent Variable:	Price knowledge		$\ln q_1$		$\ln q_0$	
	Coeff. s	Std. Errors	Coeff. s	Std. Errors	Coeff. s	Std. Errors
$\widehat{\ln mp}$	-0.074	(0.999)	-1.438**	(0.418)	-0.050	(0.422)
ln household income	0.057	(0.046)	0.122**	(0.021)	0.12 5**	(0.027)
Household size = 2	0.209**	(0.052)	0.269**	(0.035)	0.400**	(0.044)
Household size = 3	0.313**	(0.065)	0.446**	(0.047)	0.571**	(0.050)
Household size = 4	0.219**	(0.072)	0.562**	(0.046)	0.666**	(0.049)
Household size > 4	0.266**	(0.099)	0.755**	(0.058)	0.772**	(0.066)
Age	0.008**	(0.002)	0.005**	(0.001)	0.003*	(0.001)
Female	-0.314**	(0.042)	-0.010	(0.029)	-0.026	(0.039)
College degree	-0.005	(0.037)	-0.036*	(0.014)	-0.044*	(0.021)
Home ownership	0.052	(0.046)	0.168**	(0.030)	0.249**	(0.035)
Rural area	0.084	(0.052)	0.137**	(0.027)	0.093**	(0.032)
East Germany	0.006	(0.062)	-0.060*	(0.029)	-0.063	(0.036)
Year 2012	-0.015	(0.056)	0.056**	(0.019)	0.003	(0.018)
Supplier change	0.281**	(0.038)	–	–	–	–
IVM1	–	–	-0.087	(0.118)	–	–
IVM0	–	–	–	–	-0.030	(0.134)
# observations:	5,598		3,515		2,083	

Note: Standard errors are bootstrapped; * and ** denote statistical significance at the 5% and 1% level, respectively. Mean number of observations per household: 1,84.

The probit estimation results, reported in the first column of Table 3, indicate that whether a household changed its electricity provider during the three years prior to the interview is positively correlated with its price knowledge. Contrary to our prior, though, self selection does not seem to be an important issue here, as both coefficient estimates on the inverse Mills ratios are not statistically significant. In fact, the estimation results displayed on the right-hand panel of Table 3 are very close to the random-effects IV estimates originating from a separate estimation of structural Equation 3 for Group 0 and Group 1 (see Table A.2 in the appendix), where selection issues are ignored.

Sample selection issues notwithstanding, both the switching regression model and separate estimations of structural Equation 3 for both price-aware and price-ignorant households indicate that households with a crude idea about current price levels (Group 1) exhibit a price-elastic demand for electricity, whereas the elasticity estimate for uninformed households (Group 0) does not differ from zero at any conventional significance level (Table 3), a finding that is in line with e. g. Gaudin (2006) and Carter and Milon (2005).

6 Policy Recommendations

Generally, the lack of price knowledge may have numerous reasons, such as inattention, high information costs, as well as search frictions (Giulietti et al., 2014; Hortaçsu et al., 2017). The consequences of such a lack of information might be substantial, not only with respect to the environmental impact. Notably, the vanishing price responsiveness due to the lack of price awareness among a substantial fraction of households reduces market efficiency (Reiss and White, 2005).

Our empirical results illustrate that, first, price measures might be effective in curtailing electricity consumption and its negative external effects, but, second, the effectiveness of price instruments may be substantially improved by fostering household's price awareness, for example by large-scale information campaigns that increase price transparency. Recognizing that tariffs including a fixed fee obscure the effective price consumers pay per kWh, we argue that political leaders should raise the saliency of the price issue and motivate suppliers to offer a simple tariff in their portfolio that does not include a fixed fee, but is based on a sole price element: the price per kWh.

Such a tariff, for which the per-kWh price is necessarily higher than for a tariff scheme including fixed fees, would be highly transparent and, if its introduction is advertised as an electricity-saving tariff, may help households to diminish their electricity cost and consumption, as well as the associated environmental impact. A flat tariff with constant marginal prices would be particularly advantageous for those consumers with low electricity consumption who have to bear disproportionately high electricity costs under the standard two-component tariffs including fixed fees. Furthermore, from a socio-political perspective, it is particularly desirable that such a tariff would become the default tariff and, hence, would be offered to all those who would never change their supplier or tariff. This is typical for elder people, as they commonly lack computer skills that facilitate the change of the supplier via online portals and are more risk-averse than younger people.

In the end, given the now decade-plus history of unabated electricity cost increases, coupled with the prospect that this trend will continue into the foreseeable future due to Germany's strong commitment to further support renewable energy technologies (Andor et al., 2017a), the introduction of a highly transparent flat tariff may be a promising avenue to reduce the residential sector's electricity consumption and the associated environmental impact. According to the price response estimates presented here, the introduction of this kind of tariff will be particularly effective if it is advertised to foster transparency and to increase price awareness.

7 Summary and Conclusions

Consistently estimating consumer demand responses is frequently hampered by the prevalence of tariffs that include a fixed fee. Such tariffs are standard in numerous retail markets, such as telecommunications and electricity markets. The well-known endogeneity problem arising from such a tariff structure is aggravated when consumers are free to choose from a broad range of tariffs, as is common in Germany since the liberalization of European electricity markets in 1998.

To cope with the endogeneity originating from households' free tariff choice, this article has employed an instrumental-variable (IV) approach, thereby contributing to the growing literature on the price elasticity of demand for residential electricity and the role information plays in influencing customer response to price changes. Based on panel data from the German Residential Energy Consumption Survey (GRECS) for the years 2011 and 2012, the IV estimate of the price elasticity of electricity demand of about -0.52 indicates that, in general, households seem to respond to power price changes.

This general conclusion, however, does not hold unequivocally: By additionally exploiting sample information on the households' knowledge about power prices and combing the IV approach with an Endogenous Switching Regression Model, we reach the more differentiated conclusion that price knowledge is crucial for demand response. In line with Wolak (2011) and Jessoe and Rapson (2014), who find that information provision changes the price elasticity of electricity demand, our results indicate that only those households that are informed about prices are sensitive to price changes, whereas the electricity demand of uninformed households is entirely price-inelastic.

Our finding of a strong heterogeneity in households' price responsiveness suggests that further increases in power prices, which are a likely consequence of Germany's ambitious transition of its energy system (Andor et al., 2017a), lead to substantial demand reductions and, hence, environmental benefits only if households are aware of prices and their changes. In this respect, our empirical results are in line with those of He and Reiner (2017), who find that the moderate supplier switching behavior of British households can be partly traced to consumer's lack of attention to energy prices.

In addition to non-price interventions, such as social norm comparisons, which have proved to be cost-effective in the U. S. (Allcott, 2011), we therefore propose fostering low-cost information measures to increase the price awareness of households, not least because providing price information has the potential to improve market efficiency. Most notably, although utilities in a liberalized market are free in their electricity tariff design, we argue that political leaders should motivate suppliers to offer a simple tariff entailing a flat marginal price as the sole price element and couple this with large-scale public information campaigns targeted at consumers. Such a tariff, for which the per-kWh price is necessarily higher than for a tariff scheme including fixed fees, would be highly transparent and may help price-aware households to diminish their electricity cost and consumption, as well as the associated environmental impact, particularly if its introduction is advertised as an electricity-saving tariff.

Appendix

Table A.1: **Fixed-Effects Panel Estimation Results for Logged Annual Consumption**

Dependent Variable:	Standard Fixed-Effects Estimation $\ln q$		Fixed-Effects IV Estimations First Stage $\ln mp$		Second Stage $\ln q$	
	Coeff.s	Std. Errors	Coeff.s	Std. Errors	Coeff.s	Std. Errors
$\ln z$	–	–	0.069*	(0.032)	–	–
$\ln mp$	0.005	(0.046)	–	–	–	–
$\widehat{\ln mp}$	–	–	–	–	-3.200	(1.711)
Household size = 2	0.139**	(0.034)	-0.026*	(0.012)	0.061	(0.063)
Household size = 3	0.183**	(0.041)	-0.027*	(0.014)	0.102	(0.070)
Household size = 4	0.252**	(0.051)	-0.016	(0.016)	0.205**	(0.071)
Household size > 4	0.355**	(0.087)	0.007	(0.019)	0.381**	(0.101)
Age	-0.005	(0.004)	0.040**	(0.002)	0.133	(0.074)
# observations:	5,756		5,756		5,756	

Note: Standard errors are clustered at the post code level; * and ** denote statistical significance at the 5% and 1% level, respectively; employed number of observations per household: 2; Kleibergen-Paap F statistic: 4.52.

Table A.2: **Random-Effects Estimation Results for the Entire and the Split Sample, where the Sample is Split according to Price Knowledge.**

	Entire Sample		Split Sample			
			Price knowledge = 1		Price knowledge = 0	
Dependent Variable:	$\ln q$		$\ln q_1$		$\ln q_0$	
	Coeff.s	Std. Errors	Coeff.s	Std. Errors	Coeff.s	Std. Errors
$\ln f$	0.023**	(0.006)	–	–	–	–
$\ln mp$	-0.062	(0.036)	–	–	–	–
$\widehat{\ln mp}$	–	–	-1.430**	(0.418)	-0.051	(0.437)
ln household income	0.149**	(0.018)	0.125**	(0.025)	0.126**	(0.032)
Household size = 2	0.332**	(0.022)	0.280**	(0.032)	0.404**	(0.031)
Household size = 3	0.504**	(0.025)	0.463**	(0.036)	0.578**	(0.038)
Household size = 4	0.609**	(0.027)	0.574**	(0.040)	0.671**	(0.041)
Household size > 4	0.749**	(0.037)	0.770**	(0.055)	0.778**	(0.060)
Age	0.005**	(0.001)	0.005**	(0.001)	0.003**	(0.001)
Female	-0.031*	(0.015)	-0.025	(0.027)	-0.032	(0.027)
College degree	-0.023	(0.014)	-0.036*	(0.018)	-0.044	(0.025)
Home ownership	0.199**	(0.017)	0.171**	(0.024)	0.250**	(0.030)
Rural area	0.107**	(0.017)	0.142**	(0.026)	0.095**	(0.032)
East Germany	-0.095**	(0.018)	-0.060*	(0.030)	-0.062*	(0.030)
Year 2012	-0.001	(0.004)	0.055**	(0.018)	0.002	(0.019)
# observations:	6,528		3,515		2,083	

Note: Standard errors are bootstrapped; * and ** denote statistical significance at the 5% and 1% level, respectively. Employed number of observations per household: 1,84.

References

Alberini, A., Fillipini, M., 2011. Response of Residential Electricity Demand to Price: The Effect of Measurement Error. *Energy Economics* 33 (5), 889–895.

Allcott, H., 2011. Social Norms and Energy Conservation. *Journal of Public Economics* 95 (9-10), 1082–1095.

Andor, M. A., Frondel, M., Vance, C., 2017a. Germany's Energiewende: A Tale of Increasing Costs and Decreasing Willingness-To-Pay. *Energy Journal* 38 (S1), 211–228.

Andor, M. A., Frondel, M., Vance, C., 2017b. Mitigating Hypothetical Bias: Evidence on the Effects of Correctives from a Large Field Study. *Environmental and Resource Economics* 68 (3), 777–796.

Baker, P., Blundell, R., Micklewright, J., 1989. Modelling Household Energy Expenditures Using Micro-Data. *Economic Journal* 99 (397), 720–738.

Bauer, T. K., Fertig, M., Schmidt, C. M., 2009. Empirische Wirtschaftsforschung, Eine Einführung. Springer, Berlin Heidelberg.

BDEW, 2017. Erneuerbare Energien und das EEG: Zahlen, Fakten, Grafiken (2017). Bundesverband der Energie- und Wasserwirtschaft, Berlin.

BDEW, 2018. Bruttostromerzeugung im ersten Halbjahr 2018. Bundesverband der Energie- und Wasserwirtschaft, Berlin.

BNetzA, 2017. Monitoring Report 2017. Bundesnetzagentur, Bonn.

Borenstein, S., 2009. To What Electricity Price do Consumers Respond? Residential Demand Elasticity Under Increasing-Block Pricing. Preliminary draft, University of California.

Bound, J., Jaeger, D. A., Baker, R., 1993. The Cure Can be Worse Than the Disease: A Cautionary Tale Regarding Instrumental Variables. Working paper, National Bureau of Economic Research, Cambridge, Massachusetts.

Bound, J., Jaeger, D. A., Baker, R. M., 1995. Problems With Instrumental Variables Estimation When the Correlation Between the Instruments and the Endogenous Explanatory Variable is Weak. *Journal of the American Statistical Association* 90 (430), 443–450.

Cameron, A. C., Trivedi, P. K., 2009. Microeconometrics Using STATA.

Carter, D. W., Milon, J. W., 2005. Price Knowledge in Household Demand for Utility Services. *Land Economics* 81 (2), 265–283.

Chao, J. C., Swanson, N. R., 2005. Consistent Estimation With a Large Number of Weak Instruments. *Econometrica* 73 (5), 1673–1692.

Davidson, R., MacKinnon, J. G., 1989. Testing for Consistency Using Artificial Regressions. *Econometric Theory* 5 (3), 363–384.

Destatis, 2014. Eigentümerquote 2011.
URL `www.destatis.de/DE/ZahlenFakten/GesellschaftStaat/EinkommenKonsumLebensbedingungen/Wohnen/Wohnen.html`

Destatis, 2015. Einkommen, Einnahmen und Ausgaben privater Haushalte im Zeitvergleich.
URL `www.destatis.de/DE/ZahlenFakten/GesellschaftStaat/EinkommenKonsumLebensbedingungen/EinkommenEinnahmenAusgaben/Tabellen/Deutschland.html`

Espey, J. A., Espey, M., et al., 2004. Turning on the Lights: A Meta-Analysis of Residential Electricity Demand Elasticities. *Journal of Agricultural and Applied Economics* 36 (1), 65–82.

Eurostat, 2017. Electricity price statistics. European Commission, Luxemburg.

Fell, H., Li, S., Paul, A., 2014. A New Look at Residential Electricity Demand Using

Household Expenditure Data. *International Journal of Industrial Organization* 33, 37–47.

Frondel, M., Sommer, S., Vance, C., 2015. The Burden of Germany's Energy Transition: An Empirical Analysis of Distributional Effects. *Economic Analysis and Policy* 45, 89–99.

Gaudin, S., 2006. Effect of Price Information on Residential Water Demand. *Applied Economics* 38 (4), 383–393.

Giulietti, M., Waterson, M., Wildenbeest, M., 2014. Estimation of Search Frictions in the British Electricity Market. *Journal of Industrial Economics* 62 (4), 555–590.

Harding, M., Lamarche, C., 2016. Empowering Consumers Through Data and Smart Technology: Experimental Evidence on the Consequences of Time-of-Use Electricity Pricing Policies. *Journal of Policy Analysis and Management* 35 (4), 906–931.

Hausman, J. A., 1978. Specification Tests in Econometrics. *Econometrica* 46 (6), 1251–1271.

He, X., Reiner, D., 2017. Why Consumers Switch Energy Suppliers: The Role of Individual Attitudes. *Energy Journal* 38 (6), 25–53.

Hortaçsu, A., Madanizadeh, S. A., Puller, S. L., 2017. Power to Choose? An Analysis of Consumer Inertia in the Residential Electricity Market. *American Economic Journal: Economic Policy* 9 (4), 192–226.

Ito, K., 2014. Do Consumers Respond to Marginal or Average Price? Evidence From Nonlinear Electricity Pricing. *American Economic Review* 104 (2), 537–563.

Jessoe, K., Rapson, D., 2014. Knowledge is (Less) Power: Experimental Evidence From Residential Energy Use. *American Economic Review* 104 (4), 1417–1438.

Kleibergen, F., Paap, R., 2006. Generalized Reduced Rank Tests Using the Singular Value Decomposition. *Journal of Econometrics* 133 (1), 97–126.

Labandeira, X., Labeaga, J. M., Rodriguez, M., 2006. A Residential Energy Demand System for Spain. *Energy Journal* 27 (2), 87–112.

Maddala, G. S., 1983. Limited-Dependent and Qualitative Variables in Econometrics. Cambridge University Press.

Martin, S., Rivers, N., 2018. Information Provision, Market Incentives, and Household Electricity Consumption: Evidence from a Large-Scale Field Deployment. *Journal of the Association of Environmental and Resource Economists* 5 (1), 207–231.

Matsukawa, I., 2004. The Effects of Information on Residential Demand for Electricity. *Energy Journal* 25 (1), 1–17.

Pon, S., 2017. The Effect of Information on TOU Electricity Use: An Irish Residential Study. *Energy Journal* 38 (6), 55–79.

Reiss, P. C., White, M. W., 2005. Household Electricity Demand, Revisited. *Review of Economic Studies* 72 (3), 853–883.

Ros, A. J., 2017. An Econometric Assessment of Electricity Demand in the United States Using Utility-Specific Panel Data and the Impact of Retail Competition on Prices. *Energy Journal* 38 (4), 73–98.

RWI, forsa, 2015. The German Residential Energy Consumption Survey 2011-2013. RWI Projektberichte.

RWI, forsa, 2018. The German Residential Energy Consumption Survey.
URL `www.rwi-essen.de/haushaltsenergieverbrauch`

Schulte, I., Heindl, P., 2017. Price and Income Elasticities of Residential Energy Demand in Germany. *Energy Policy* 102, 512–528.

Shin, J.-S., 1985. Perception of Price when Price Information is Costly: Evidence from Residential Electricity Demand. *Review of Economics and Statistics* 67 (4), 591–598.

Spees, K., Lave, L. B., 2007. Demand Response and Electricity Market Efficiency. *Electricity Journal* 20 (3), 69–85.

Stock, J. H., Yogo, M., 2005. Testing for Weak Instruments in Linear IV Regression. *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*.

Taylor, L. D., 1975. The Demand for Electricity: A Survey. *Bell Journal of Economics* 6 (1), 74–110.

Taylor, R. G., McKean, J. R., Young, R. A., 2004. Alternate Price Specifications for Estimating Residential Water Demand With Fixed Fees. *Land Economics* 80 (3), 463–475.

Vesterberg, M., Krishnamurthy, C. K. B., 2016. Residential End-Use Electricity Demand: Implications for Real Time Pricing in Sweden. *Energy Journal* 37 (4), 141–164.

Wolak, F. A., 2011. Do Residential Customers Respond to Hourly Prices? Evidence From a Dynamic Pricing Experiment. *American Economic Review* 101 (3), 83–87.