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Switching Response to Power Prices: Evidence from German Households

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1 Introduction

Electricity prices for German households have virtually doubled since the beginning of the new millennium, when prices reached their minimum after the liberalization of the electricity market in 1998. One of the consequences of this liberalization was the opportunity for households to, for the first time, freely determine their electricity provider of choice. Yet, despite such elements to improve competition, household prices have steadily increased after 2000, with the introduction of new taxes and levies being a major reason (BNetzA, 2014). Currently, taxes and levies account for more than half of power prices for German households.

For instance, to stabilize the contribution rates to pension insurances with the resulting revenues, an eco-tax on electricity was raised in 1999, with the tax rate being doubled in 2003. Another key reason for rising power prices was the introduction of a feed-in tariff support scheme for renewable electricity technologies in 2000. While this support scheme was very effective in increasing the share of green electricity in gross consumption, from less than 7% in 2000 to 27,8% in 2014, the resulting burden for consumers has particularly mounted in recent years, above all due to the exploding expansion of photovoltaics 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 2014, and increased from 1,31 cents per kilowatt-hour (kWh) to 6,24 cents/kWh. In the meanwhile, the electricity prices that have to be borne by German households are – in terms of purchasing power parities – the highest in the European Union (Eurostat, 2014).

Empirical evidence on the response of German households to electricity price increases, however, is sparse. Using data from Germany's Residential Energy Consumption Survey (GRECS) for 2011 and 2012, we fill this void by employing an instrumental variable (IV) approach to cope with the endogeneity of the consumers' tariff choice. As instruments for the likely endogenous price variables, we use the sum of local grid fees, taxes and levies. Our instruments should be valid, as they are, first, strongly

correlated with the customer prices and, second, are not affected by consumers tariff choice or consumption patterns.

Moreover, by exploiting our information on the households' knowledge about power prices, we additionally employ an Endogenous Switching Regression Model to estimate price elasticities for two groups of households: those that indicate that they are informed about current price levels and those that are unaware of prices. With elasticity estimates falling between -0.92 and zero, we find the German residential electricity demand to be quite inelastic. Our switching regression results indicate that price knowledge is essential for demand response.

The subsequent Section 2 provides a literature review on the price elasticities of residential demand for electricity. In Section 3, we provide a short summary of our database, followed by the presentation of our estimation results in Section 4 and 5. The final section closes with a summary and conclusions.

2 Findings from the Literature

The demand for electricity has been investigated by economists for more than 60 years, resulting in a large body of empirical studies. Yet, no broad consensus has been reached about the size of the response of residential electricity demand to changing power prices, which is typically captured by estimates of price elasticities. While the bulk of studies provides estimates for the US, the results are strongly divergent: even for the same region and similar time periods, there are huge differences in elasticity estimates. In an early survey article, Taylor (1975) reports elasticity estimates ranging from -0.89 to -0.13 in the short run and from -2.0 to zero in the long run. Numerous studies followed for the US, such as Shin (1985), Terza (1986), Reiss and White (2005), and Fell et al. (2014), that also provide for a large variety of elasticity estimates, with estimates turning out to be as low as -2.01.

A key reason for these discrepancies is the specification of the price variable. While

theory would predict that consumers optimize with respect to marginal prices, empirical findings suggest that consumers tend to react to other price measures. Ito (2012), for example, finds strong evidence that households respond to average prices, rather than marginal or expected marginal prices. By empirically investigating the same issue, Borenstein (2009) comes to similar conclusions, thereby claiming that consumers do not respond to marginal prices due to missing price knowledge. Particular attention received the issue of the usage of marginal and/or average prices under increasing or decreasing block pricing, as this was, and still is, the dominant tariff structure in the US (Barnes et al., 1981; Terza and Welch, 1982; Jones and Morris, 1984; Shin, 1985; Terza, 1986; Baker et al., 1989).

Closely related to the debate on what price measures consumers respond to is the discussion on the effects of their knowledge about prices. Gaudin (2006), for instance, analyzes the effect of more detailed information on prices emerging from water bills, finding that households with price knowledge are considerably more price-elastic than price-ignorant households. In a similar vein, using a switching regression approach, Carter and Milon (2005) examine the effect of price knowledge for various utility services and also come up with the result that informed households are more responsive than those without any clue about prices.

Much less empirical evidence is available for countries other than the US. Among just a few studies are Hondroyiannis (2004) and Halicioglu (2007), who find long-run electricity price elasticities of -0.41 and -0.52 for Greece and Turkey, respectively, as well as Labandeira et al. (2005) and Filippini (1999), whose elasticity estimates for Spain and Switzerland amount to -0.79 and -0.30, respectively. Using detailed household data, our study adds to this strand of the literature by providing price elasticity estimates of residential electricity demand for Germany, for which, apparently, no such estimates have been published thus far.

A contentious issue that received significant attention in the literature is the role of fixed fees. This issue is also relevant for our analysis, as the common pricing model

in the German retail market for electricity includes two components: a monthly fixed fee and a constant marginal price per kilowatt-hour (kWh). While Baker et al. (1989) claims that fixed fees may only cause small bias, 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 p_a as the price measure, with the average price being defined as follows:

$$p_a := \frac{p_m q + f}{q}, \quad (1)$$

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

In fact, it is straightforward to show that the price elasticity of demand $\frac{\partial \ln q}{\partial \ln p_a}$ approaches -1 if the price measure underlying this estimate is the average price p_a and if it is much larger than the marginal price p_m : $p_a \gg p_m$. Rearranging definition (1) yields $q = f / (p_a - p_m)$ and, hence, $\frac{\partial q}{\partial p_a} = -f / (p_a - p_m)^2 = -q / (p_a - p_m)$. Employing this derivative, the average price elasticity of demand reads:

$$\frac{\partial \ln q}{\partial \ln p_a} = \frac{p_a}{q} \cdot \frac{\partial q}{\partial p_a} = -\frac{p_a}{q} \cdot \frac{q}{p_a - p_m} = -\frac{p_a}{p_a - p_m} \quad (2)$$

$$= -1 - \frac{p_m}{p_a - p_m}, \quad (3)$$

where the last term approaches -1 for $p_a \gg p_m$. For the special case of a flat rate $f > 0$, that is, $p_m = 0$, the average price elasticity of demand, $\frac{\partial \ln x}{\partial \ln p_a}$, is identical to -1. In short, using average prices for estimating of price elasticities may lead to a massive overestimation in case of tariffs that include a fixed fee.

3 Data

Our analysis is based on detailed panel data originating from a retrospective survey of about 8,500 households conducted in 2014. In addition to electricity consumption and cost data, stemming from the households' bills for the years 2011 and 2012, our database entails rich information on socio-economic and other household characteris-

tics, such as household net income, household size, age and education of the household head, and ownership of the residence.¹ The billing information includes marginal prices per kWh, monthly fixed fees, total electricity expenditures and precise consumption levels. If several bills are available that at least partly cover the relevant year, we use all available information to calculate a household's total spending for electricity in that year and the respective annual consumption.

Average prices are calculated by dividing total spending on electricity, including monthly fixed fees, by total consumption. When marginal prices differ across the distinct bills of a household, we take the mean weighted by the billing days in the respective year. As only about one third of the more than 8,500 surveyed households were able to provide reliable information on their electricity bills from 2011 and 2012, we end up with an estimation sample of 6,865 households. All other observations have been dropped, for example, because households provided implausible or incomplete information. Moreover, we have skipped observations from households with two or more overlapping bills, as well as from households that provided information for less than 30 billing days.

Before reporting billing information, the respondents were requested to gauge the marginal price per kWh they had to pay for 2012, yet without looking at their bills. 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 the deviation of a household's ex-ante estimate is less than $\pm 20\%$ from the actual marginal price, this indicator takes on the value of 1 and 0 otherwise.² It turns out that, according to this definition, 61% of our sample households have a coarse impression of electricity prices (Table 1).

Turning to the descriptive statistics reported in Table 1, it bears noting that with

¹Income was provided in categories and recoded on class middles to derive a continuous variable. Information on whether a household resides in a rural or urban area is provided by the Federal Statistical Office (Destatis 2015) and was merged to our database.

²Alternative bandwidths of $\pm 10\%$ and $\pm 15\%$ have also been employed for the definition of price knowledge, leaving our estimation unaltered.

3,668 kWh, our sample households' average electricity consumption per annum roughly matches the annual consumption of a typical German household, which according to BNetzA (2014) amounts to about 3,500 kWh in 2014. Furthermore, the average price of 26 € Cents per kWh obtained from our sample fits well to the mean household price of 26.8 € Cents that is published by Eurostat (2014) for the second half of 2012. With 3,041 € per month, the mean net income of our sample households is very close to the 3,069 € that are reported as average income for German households for 2012 by the German Federal Statistical Office (Destatis, 2015).

Unlike electricity consumption, prices, and net income, the share of home owners in our sample is not representative for Germany: With 66%, the sample share of home owners is far higher than the share of 45.9% that is published by the German Federal Statistical Office (Destatis, 2014b). 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 home owners, not least due to the fact that tenants move more frequently than home owners. Not surprisingly, as it was the household heads and, hence, exclusively adult household members who were asked to respond to our survey, the respondents' mean age of 56.17 years is larger than the average of 45.9 years for the German population (Destatis, 2014a).

Finally, to instrument our likely endogenous price variables originating from the survey, we add information on local grid fees, taxes and levies. The data was gathered by ene't, a professional provider of energy related data. We include Information on grid fees, eco-tax, EEG-surcharge, concession levy, CHP-surcharge and some further minor levies. Overall the included grid fees, taxes and levies account for nearly 50 percent of the average consumer price. While grid fees significantly differ across regions, taxes and levies are mainly time variant. The partial correlation coefficient of 0.23 also indicates a positive correlation with consumers' marginal prices. We have merged this information to our data by postcode region.

Table 1: Descriptive Statistics

	Mean	Standard Deviation	Minimum	Maximum
Consumption	3,668.1	2,088.19	679.57	26,535
Marginal price	0.20	0.03	0.12	0.28
Average price	0.26	0.03	0.15	0.40
Taxes, levies	0.12	0.01	0.1	0.17
Net income	3,041.81	1,413.07	450	6,500
Age	56.17	12.9	18	86
Ownership	0.66	–	0	1
Rural Area	0.20	–	0	1
West/ost	0.16	–	0	1
Supplier Change	0.35	–	0	1
Informed	0.61	–	0	1

Note: Number of observations: 6,865. Annual consumption is measured in kWh, prices and net monthly household income are in €.

If there is more than one energy distribution grid in a postcode region, we refer to the largest according to the number of customers in the respective region. If grid fees, taxes or levies change during a year we take the average weighted by days of validity in the respective year.

4 Methodology and Estimation Results

In line with the debate on the kind of price measure that is relevant for consumer decisions, we employ two price measures in our estimations: actual marginal and average prices. To provide for a reference case, we use the random effect method and estimate a double-log specification, which is typically employed for elasticity estimations:

$$\ln(q_{it}) = \alpha + \alpha_p \cdot \ln(p_{it}) + \alpha \cdot \mathbf{x}_{it} + \gamma_i + \varepsilon_{it}, \quad (4)$$

where $\ln(q_{it})$ denotes the natural logarithm of the annual electricity consumption q_{it} of household i at time t , p_{it} stands for alternative price measures, the marginal or average price, x_{it} is a vector of household characteristics, γ_i is a household random effect and ε designates the error term. Using this specification has the advantage that price elasticity estimates can be immediately gleaned from the estimated coefficients of the price variables.

4.1 RE-Estimation Results

Our random-effects estimation results for structural equation 4 indicate that both marginal and average prices have statistically significant effects on electricity demand (Table 2). Note also that with -0.86, the demand elasticity with respect to average prices is considerably larger than that for marginal prices, which is quite close to zero: -0.07. Yet, our elasticity estimate of -0.86 is in line with Taylor et al. (2004), who demonstrate that estimations using average prices are biased towards -1. This casts doubt on the usage of average prices as the preferred price measure and, hence, in what follows, we focus on marginal prices as our price measure of choice.

Table 2: Ordinary Least Squares Estimation Results.

Dependent Variable:	Logged Annual Electricity Consumption	
Logged marginal price	-0.0721*	–
	(0.0387)	–
Logged average price	–	-0.8592***
	–	(0.0427)
Logged hh income	0.1118***	0.0994***
	(0.0153)	(0.0144)
HH size	0.5633***	0.5043***
	(0.0161)	(0.0152)
Age	0.2878***	0.2645***
	(0.0258)	(0.0242)
Ownership	0.2012***	0.1825***
	(0.0152)	(0.0141)
Rural area	0.0818***	0.0944***
	(0.0152)	(0.0142)
Ost	-0.0972***	-0.0612***
	(0.0172)	(0.0164)
Year dummie	Yes	Yes
Education dummies	Yes	Yes
Number of observations	6,865	6,865

*Note: Standard errors are in parentheses and clustered at the post code level; * denotes significance at the 10% level, ** at the 5% level, *** at the 1% level, respectively.*

4.2 IV Estimates

Before 1998, a monopolistic market prevailed in Germany in which regional and local monopolists – protected by law – dictated their prices to consumers. In this regime, households had no opportunity at all to choose their provider and tariff, but stuck to their local electricity provider, and, thus, electricity prices were clearly exogenous to households. Traditional price structures included a monthly fixed fee, as well as a constant marginal price that was independent of consumption levels.

In 1998, Germany's electricity market was liberalized and a retail market started to establish. Today, households are free to choose from a wide variety of providers and tariffs, the dominant tariff structure remained the same: common price structures consist of a monthly fixed fee and a constant marginal price, whereas alternatives, such as package and flat-rate tariffs, are rarely offered. Yet, even almost two decades after liberalization, the majority of German households are still customers of their local provider, more often than not paying expensive so-called basic tariffs. This seems to be a strong indication that prices do not necessarily enjoy the highest priority when it comes to the selection of an electricity provider.

This hypothesis is confirmed by the estimation results originating from our instrumental variable (IV) approach, which indicates a price-inelastic electricity demand (Table 3). With this IV approach, we seek to cope with simultaneity problems that may arise if households actually take advantage of their option to choose among a large variety of providers and tariffs. In this case, both the fixed fee and the marginal price can be expected to be endogenous, since rational customers with a large consumption would be willing to accept a high fixed fee in favor of a low marginal price, whereas those with a low consumption will prefer tariffs with a low fixed fee, but a relatively large marginal price. In short, while on the one hand consumption may be affected by prices, on the other hand, tariff selection may depend on consumption levels, thereby yielding a problem of simultaneity.

As an instrument z for the likely endogenous marginal price, we employ the sum

of grid fees, taxes and levies in the respective region in the respective year. The grid fees, taxes and levies are strongly correlated with the prices that our households had to pay, since they account for more than 50 percent of the observed consumer prices. Still they can be assumed to be exogenous since they are not affected by households tariff choice or consumption patterns. Hence, our instrument z should neither affect the dependent variable q aside from its correlation with p , nor should it be correlated with the error term, ε . In short, both identification assumptions for valid instruments should hold: (1) $Cov(p, z) \neq 0$ and (2) $Cov(\varepsilon, z) = 0$.

Although the IV estimates should be estimated by a one-stage regression to obtain correct standard errors (Wooldridge, 2006, p.526), it is illuminating and helpful for our estimations in the subsequent section to conceive the IV estimation as a two-stage estimation procedure. In the first stage, the marginal price p is regressed on our instrumental variable z , the local suppliers' marginal prices, and the vector x of household characteristics:

$$\ln(p_{it}) = \beta + \beta_z \cdot \ln(z_{it}) + \beta \cdot x_{it} + v_{it}, \quad (5)$$

where v designates the error term. In the second stage of the IV approach, instead of employing observed prices p , structural Equation 4 is estimated using the predictions $\widehat{\ln p}$ that are obtained from estimating first-stage Equation 5.

From the first-stage regression of Equation 5, we learn that our instrument z , the local grid fees, taxes and levies, is positively correlated with the prices p the households paid (Table 3), as $\ln z$ is statistically significant at the 1% level. From this result, it can be concluded that the first assumption for valid instruments holds: $Cov(p, z) \neq 0$. The results of the second stage regression show an inelastic demand with respect to instrumented marginal prices. A 1 percent increase in power marginal prices comes along with a 0.5 percent decrease in energy consumption.

An important drawback of IV estimates is that the related 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 were actually to be exogenous, the IV

Table 3: Instrumental Variable (IV) Estimation Results.

	IV Estimation	
	First Stage	Second Stage
Taxes, levies	0.5265*** (0.0314)	– –
$\widehat{\ln p}$	– –	-0.5074*** (0.1189)
Logged hh income	-0.0208*** (0.0040)	0.1037*** (0.0160)
Hh size	-0.0042 (0.0043)	0.5658*** (0.0165)
Age	-0.0297*** (0.0070)	0.2808*** (0.0263)
Ownership	-0.0093** (0.0043)	0.1810*** (0.0157)
Rural area	0.0283*** (0.0044)	0.0975*** (0.0162)
Ost	-0.0083 (0.0056)	-0.0871*** (0.0178)
Year dummy	Yes	Yes
Education dummies	Yes	Yes
Number of observations	6,865	6,865

*Note: Standard errors are in parentheses and clustered at the post code level; * denotes significance at the 10% level, ** at the 5% level, *** at the 1% level, respectively.*

estimator would still be consistent, but less efficient than the OLS estimator. Moreover, if an instrument is only weakly correlated with an endogenous regressor, the standard errors of IV estimators are even much larger, so that the loss of precision will 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 5 is correlated with the error term ε of structural Equation 4. 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 $\hat{\nu}$ as an additional regressor into structural Equation 4 and test its statistical significance (Davidson and MacKinnon, 1989). As a result, we get a coefficient estimate that is significant at the 1% 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 household observations are clustered at the household level, a statistical test for weak instruments is based on a Wald test and the rk statistic of Kleibergen and Paap (2006). With an F statistic of $F = 24.48$ for the coefficient β_z of the first-stage regression, which is well above the threshold of 16.38 given by Stock and Yogo (2005), we can reject the null hypothesis of weak identification. Lastly, tests on over-identification are obsolete, as we use just one instrument z for the endogenous variable p .

5 The Effect of Price Knowledge

Exploiting our information on the households' knowledge about power prices, we now employ an Endogenous Switching Regression Model (Maddala, 1983, 223-228) to estimate price responses for two groups of households, those that are informed about current price levels (Group 1) and those that are unaware of prices (Group 0):³

$$\text{info} = \begin{cases} 1 & \text{if } \gamma \cdot \mathbf{w}_i \geq u_i, \\ 0 & \text{otherwise,} \end{cases} \quad (6)$$

In this definition, \mathbf{w}_i denotes those household characteristics that may affect whether a household is informed about prices (Group 1: info=1), 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, as there may be unobservable factors that are relevant for both the selection into either group and the consumption level.

In line with structural Equation 4, the behavioral response of households due to price changes is described by two equations:

$$\ln(q_{1it}) = \alpha_1 + \alpha_{1p} \cdot \ln(p_{it}) + \boldsymbol{\alpha}_1 \cdot \mathbf{x}_{1it} - \sigma_{1u} \cdot \text{IVM}_{1i} + \eta_{1it} \quad \text{if info} = 1, \quad (7)$$

$$\ln(q_{0it}) = \alpha_0 + \alpha_{0p} \cdot \ln(p_{it}) + \boldsymbol{\alpha}_0 \cdot \mathbf{x}_{0it} + \sigma_{0u} \cdot \text{IVM}_{0i} + \eta_{0it} \quad \text{if info} = 0, \quad (8)$$

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

$$\text{IVM}_{1i} := \frac{\phi(\boldsymbol{\gamma}^T \cdot \mathbf{z}_i)}{\Phi(\boldsymbol{\gamma}^T \cdot \mathbf{z}_i)}, \quad \text{IVM}_{0i} := \frac{\phi(\boldsymbol{\gamma}^T \cdot \mathbf{z}_i)}{1 - \Phi(\boldsymbol{\gamma}^T \cdot \mathbf{z}_i)} \quad (9)$$

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

³To this end, we have employed the stata command `movestay` (Lokshin and Sajaia, 2004).

When appended as extra regressors in the second-stage estimation, the inverse Mills ratios are controls for potential biases arising from sample selectivity: It is likely that intrinsically unobservable characteristics, such as carelessness about electricity bills, also affect WTP bids. If the estimated coefficients – σ_{1u} and σ_{0u} – are statistically significant, this is an indication of sample selectivity. For the second-stage estimation, we insert the predicted values \widehat{IVM}_{1i} and \widehat{IVM}_{0i} using the probit estimates $\hat{\gamma}$ of the first-stage estimation.

Identification of the switching regression model requires at least one variable that determines price knowledge of the respondents, yet not their electricity consumption level. Such a variable would fulfill what is commonly called the exclusion restriction. Whether a household changed its electricity provider during the last three years (Supplier Change = 1) is a candidate variable for the exclusion restriction, as households, while searching for a new provider, may gather information on tariffs and prices and, hence, acquire price knowledge.

The endogenous switching regression model is estimated using the full information maximum likelihood (FIML) estimator (Lee (1978)), as it is more efficient than two-stage least squares and the maximum likelihood estimator and provides consistent standard errors (Lokshin and Sajaia, 2004). To account for the endogeneity of marginal prices, we again employ the predicted marginal prices $\widehat{\ln p}$ resulting from Equation 5, rather than observed marginal prices, thus combining IV methods with the switching regression model.

The probit estimation results for the first stage 6 of the switching regression model reported in Column 1 of Table 4 show that whether a household changed its electricity provider during the previous three years positively impacts its price knowledge, with the corresponding coefficient estimate being statistically significant at the 1% level. According to these results, changing the supplier increases the probability that a household is informed about price levels by 28,1 percentage points relative to those that stuck to their provider during the previous three years. In line with the literature (Gaudin,

Table 4: Switching Regression Estimations Results.

Dependent Variable:	First Stage info = 1	Group 1 $\ln(q_1)$	Group 0 $\ln(q_0)$
$\widehat{\ln p}$	–	-0.9155*** (0.2398)	-0.0296 (0.2716)
Logged hh income	0.0807** (0.0385)	0.0860*** (0.0235)	0.0842*** (0.0292)
Hh size	0.1868*** (0.0411)	0.5305*** (0.0274)	0.5792*** (0.0334)
Age	0.5073*** (0.0641)	0.2913*** (0.0500)	0.1550** (0.0631)
Ownership	0.0831** (0.0399)	0.1538*** (0.0220)	0.2388*** (0.0292)
Rural area	0.0825** (0.0410)	0.1109*** (0.0228)	0.0554* (0.0322)
Ost	0.0023 (0.0464)	-0.0941*** (0.0258)	-0.0637** (0.0316)
Supplier change	0.2812*** (0.0357)	–	–
Year dummy	Yes	Yes	Yes
Education dummies	Yes	Yes	Yes
Number of observations	5,840	3,589	2,251

*Note: Standard errors are in parentheses and clustered at the post code level; * denotes significance at the 10% level, ** at the 5% level, *** at the 1% level, respectively.*

2006; Carter and Milon, 2005), we find evidence that households with a crude idea about current price levels (Group 1) are much more price elastic than price-ignorant households (Group 0). While households with price knowledge show a price elasticity of -0,92, we can not find a significant price elasticity for price-ignorant households.

6 Summary and Conclusions

The demand response of households to electricity price changes is a understudied issue in Germany, where apparently no such elasticity estimates are available. Using comprehensive data from Germany's Residential Energy Consumption Survey (GRECS) for 2011 and 2012, we have employed an instrument variable (IV) approach to cope with the endogeneity of the consumers' tariff choice. Our IV-estimates indicate a rather price inelastic demand with a price elasticity of -0.51.

By additionally exploiting our information on the households' knowledge about power price and employing an Endogenous Switching Regression Model, we come up with the conclusion that price knowledge is essential for demand response. Hence, increasing households' knowledge on power prices may increase their price sensitivity. With respect to the external effects of electricity generation, our findings of a quite inelastic demand suggest that further increases in power prices do only lead to substantial demand reductions and, hence, significant benefits for the environment if households acquire better price knowledge. Thus, increasing households price knowledge may have larger effects on electricity demand than further price increases.

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