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Heterogeneity in the price response of residential electricity demand: A dynamic approach for Germany

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Heterogeneity in the Price Response of Residential Electricity Demand: A Dynamic Approach for Germany

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Manuel Frondel, Gerhard Kussel, and Stephan Sommer

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Residential Electricity Demand:
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Manuel Frondel, Gerhard Kussel, and Stephan Sommer¹

Heterogeneity in the Price Response of Residential Electricity Demand: A Dynamic Approach for Germany

Abstract

To provide the basis for evaluating the effectiveness of price policies, this paper contributes to the literature by estimating the heterogeneity in the response of residential electricity demand to price increases across household types. Drawing on household panel data from the German Residential Energy Consumption Survey (GRECS) that span over nine years (2006-2014), we gauge the response of residential electricity demand to price increases on the basis of the dynamic Blundell-Bond estimator to account for potential simultaneity and endogeneity problems, as well as Nickell bias. Estimating short- and long-run price elasticities of -0.44 and -0.66, respectively, our results indicate that price measures may be effective in dampening residential electricity consumption, particularly in the long run. Yet, we also find that responses to price changes are very heterogeneous across household groups, an outcome that has important implications for policy-making. Most notably, we do not find any significant price response for low-income households.

JEL Classification: C23, C26, D12, Q41

Keywords: Dynamic panel methods; instrumental variable approach

December 2018

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1 Introduction

Due to growing concerns about climate change, policy-makers from all around the world establish measures that aim at cutting greenhouse gas emissions. For instance, by 2030, the European Union (EU) strives for a 40% reduction in greenhouse gas emissions relative to 1990. To this end, many EU countries have implemented promotion schemes for renewable energy technologies, whose costs are borne by electricity consumers (REN21, 2017). As an alternative instrument, a few countries, such as France and Great Britain, have implemented carbon taxes on fossil fuels (RES, 2018) to diminish the use of fossil fuels and fossil-fuel-based electricity alike.

The effectiveness of such price measures, however, critically hinges on the magnitude of the demand response to increasing electricity prices. Although the demand for electricity has been analyzed for decades, a consensus on the magnitude of its price elasticity has never been reached. In fact, the empirical literature reports a wide range of price elasticity estimates of electricity demand, spanning from 0 to -2.50 (Espey et al., 2004; Krishnamurthy and Kriström, 2015).

This wide range is due to numerous reasons among which are discrepancies across empirical studies with respect to investigation periods, regional foci, the level of data aggregation, the specification of the price variable, and, not least, the econometric method employed (Alberini et al., 2011; Bernard et al., 2011; Fell et al., 2014). In this respect, it bears noting that both standard OLS and panel estimation methods fail to address the particularities of electricity demand, specifically the endogeneity of prices (Borenstein, 2009; Ito, 2014; Taylor et al., 2004) and the sluggishness in the adjustment of the appliance stock (e.g. Reiss and White, 2005).

To provide an informed, yet so far unavailable, basis for evaluating the effectiveness of price policies to reduce electricity consumption as a means to combat climate change, this paper contributes to the literature by estimating the heterogeneity in the response of residential electricity demand to price changes across household types. Inspired by concepts of behavioral economics, we establish a theoretical model in which

attention (e.g. DellaVigna, 2009) to electricity consumption issues plays a key role in explaining heterogeneity in electricity demand. While the model predicts that the consumption levels of households with inattentive heads are higher than those of other households, its predictions with respect to the responses to price changes are ambiguous. We thus argue that, ultimately, the analysis of demand responses to price changes across household groups remains an empirical issue.

To shed light on this issue, we draw on a large panel data set (2006-2014) on the electricity consumption of individual households originating from the German Residential Energy Consumption Survey (GRECS) to estimate the price responses of households on the basis of the dynamic system estimator developed by Blundell and Bond (1998). The main virtue of this estimator is to account for potential simultaneity and endogeneity problems, as well as Nickell bias. Following McFadden et al.'s (1977) suggestion to use price components as an instrument for endogenous prices, in line with Frondel and Kussel (2019), we employ the sum of the regulated price components, such as grid fees, taxes, and levies, as an instrument to cope with the likely endogeneity of electricity prices.

By comparing our preferred estimates with those resulting from both OLS and standard panel methods, we demonstrate that price elasticity estimates may be biased if methodological challenges such as the sluggishness of demand response and endogeneity issues are not adequately addressed. Our short- and long-run price elasticity estimates of -0.44 and -0.66, respectively, are in line with the scarce empirical evidence that is available for Germany. For instance, based on expenditure rather than consumption data, Nikodinoska and Schröder (2016) and Schulte and Heindl (2017) estimate long-run price elasticities of -0.81 and -0.43, respectively. Moreover, on the basis of a single survey wave of the GRECS comprising the years 2011 and 2012, for which information on households' knowledge about electricity price levels is available, Frondel and Kussel (2019) obtain a short-run price elasticity estimate of -0.52, finding that only those households that are informed about prices are sensitive to price changes, whereas uninformed households are entirely price-inelastic.

Our empirical results indicate that, particularly in the long run, price measures may be effective instruments to dampen the electricity consumption of the residential sector, which accounts for a substantial share of about 30% in the EU's electricity consumption (Eurostat, 2018). Yet, price responses turn out to be very heterogeneous: Wealthy households, as well as households with male heads and heads with college degree, exhibit a particularly strong demand reaction, whereas we do not find any significant price response for other household groups, most notably low-income households.

This heterogeneity suggests that increasing electricity prices, for instance via a carbon tax, may not be a universally effective means. Therefore, to reduce electricity consumption and the resulting greenhouse gas emissions alike, in addition to price measures, targeted energy conservation programs may be implemented that include non-pricing measures, such as means-tested subsidies for the purchase of energy-efficient appliances and information campaigns on energy conservation, and focus on those households that are hardly responsive to price increases, above all low-income households.

Given its ambitious aim to increase the share of renewable-based electricity in gross consumption to 65% by 2030, Germany suggests itself as an interesting case study for the analysis of demand reactions to power price increases. As a consequence of Germany's highly costly support scheme for the production of "green electricity" (Frondel et al., 2015), German households face the highest electricity prices in the EU in terms of purchasing power standards (Andor et al., 2017), with nominal prices averaging about 30 cents per kilowatt-hour (kWh). Since the introduction of Germany's feed-in-tariff system to promote renewable energy technologies in 2000, household electricity prices have more than doubled (BDEW, 2017). The major driver of this price increase was the levy with which electricity consumers have to bear the cost of supporting renewable energy technologies (BDEW, 2017). While Germany's support scheme has proven highly successful in raising the share of "green" electricity in (gross) electricity consumption, which increased from below 7% in 2000 to about 36% in 2017 (BMW, 2017),

2018), the levy for the support of renewable technologies rose substantially, from 0.30 to 6.79 cents per kWh in 2018, now accounting for over a fifth of household electricity prices (BDEW, 2017).

The subsequent section provides a theoretical model to explain the heterogeneity in demand responses across household groups. Section 3 describes the database underlying our research and Section 4 presents the empirical methodology employed. While Section 5 reports our estimation results for the residential sector as a whole, Section 6 presents those for specific households groups. The last section summarizes and concludes.

2 Theoretical Model

To theoretically analyze the heterogeneity in the electricity demand response to price changes across household groups, inspired by concepts of behavioral economics and Kotchen and Moore (2008), we employ a household production model in which attention to electricity issues plays a key role (see also DellaVigna, 2009). We assume that household i uses electricity in the amount of e_i as an input to produce energy services, such as lighting, and the household's demand for electricity derives from the demand for those energy services that are satisfied by electricity. Another important determinant of e_i is the energy efficiency $\eta_i(AS_i) := s_i/e_i$ of the appliance stock AS_i , where s_i designates the desired service level.

Our model is based on the simplest setup capable of illustrating that the attention that households devote to electricity issues is a key factor for the heterogeneity in demand. Attention is captured in our model by the indicator variable a_i , which equals unity if household i pays attention to the its electricity consumption level and equals zero otherwise, that is, if the household is inattentive.

We assume that the utility u_i of attentive households is negatively influenced by the attention to electricity issues, such as knowledge about the household's electricity expenditure and consumption level, because, for instance, the household is aware of

the negative external effects of electricity production based on fossil fuels. In addition to attention, the electricity price p and household income m are further key determinants of the electricity consumption level: $e_i = e_i(p, m, a_i, o_i)$, where o_i denotes other factors, such as energy efficiency η_i .

While household i is subject to the budget constraint $x_i + pe_i = m$, it seeks to maximize the additively separable utility function of the form

$$u_i(x_i, e_i, a_i) := f(x_i) + g(e_i) - a_i h(e_i), \quad (1)$$

where x_i is a numeraire consumption good that captures all other goods and services that the household demands and, for the sake of exposition, we define $g(e_i) := k(s_i) = k(\eta e_i)$, with $k(s_i)$ denoting the utility derived from energy services s_i that are based on electricity. All functions f, g, h map into \mathbb{R}_0^+ and their derivatives are strictly positive. For the second derivatives, it is assumed that $f'' \leq 0, g'' < 0$ and $h'' \geq 0$.

The first-order condition of the maximization problem

$$\max_{e_i} u_i(x_i, e_i, a_i) \quad \text{subject to} \quad x_i + pe_i = m \quad (2)$$

is given by

$$g'(e_i) = pf'(m - pe_i) + a_i h'(e_i), \quad (3)$$

implying that the marginal benefit of electricity consumption equals its marginal cost. This cost consists of the value of the forgone consumption of the numeraire good and the disutility derived from the attention to electricity consumption issues, which results, for example, from the awareness about the negative external effects of electricity production.

From First-Order Condition (3), $f' > 0$, as well as $g'' < 0$, it follows that, all else equal, high-income households have a higher electricity consumption than low-income households: $e_i^{m_h} > e_i^{m_l}$, where $e_i^{m_l}$ and $e_i^{m_h}$ denote the consumption levels of low- and high-income households, respectively. In fact, by differentiating Equation

(3) with respect to m , it follows that, in line with economic theory, the demand for electricity weakly increases with increasing household income m :

$$\frac{\partial e_i}{\partial m} = \frac{f''(m - pe_i)}{g''(e_i) + pf''(m - pe_i) - a_i h''(e_i)} \geq 0, \quad (4)$$

as the assumptions on the second derivatives of f , g and h ensure that the denominator of the fraction on the right-hand side of Equation (4) is negative and the sign of the numerator is determined by the assumption $f'' \leq 0$.

In a similar vein, by differentiating Equation (3) with respect to p , in accordance with economic theory, it follows that electricity consumption is weakly decreasing in p :

$$\frac{\partial e_i}{\partial p} = -\frac{e_i f''(m - pe_i)}{g''(e_i) + pf''(m - pe_i) - a_i h''(e_i)} \leq 0. \quad (5)$$

To investigate the heterogeneity in the demand response to price changes with respect to income, we differentiate Equation (5) with respect to m , for the sake of simplicity focusing on inattentive households ($a_i = 0$):

$$\frac{\partial^2 e_i}{\partial m \partial p} = -\frac{e_i f'''(m - pe_i)}{g''(e_i) + pf''(m - pe_i)} + \frac{e_i f''(m - pe_i)[g'''(e_i) + pf'''(m - pe_i)]}{[g''(e_i) + pf''(m - pe_i)]^2}. \quad (6)$$

Apart from the fact that assumptions for the third derivatives of f and g have to be invoked, given the complexity of the expression on the right-hand side of Equation (6), its sign remains unclear and we conclude that the demand response to price changes with respect to income becomes an empirical matter. This conclusion is in line with the literature from which two possible rationales for diverging price elasticities across different income groups emerge: On the one hand, according to Reiss and White (2005) and Silva et al. (2017), given their small budgets, low-income households would be more sensitive to electricity prices than wealthy households. But, on the other hand, it is argued that wealthier households tend to exhibit a preference for more energy-efficient appliances (Alberini et al., 2011) and are more capable of adjusting their appliance stock towards less electricity-intensive equipment as a response to

rising electricity prices (Spees and Lave, 2007). Both factors lead to an income elasticity of the electricity demand that is higher for high-income households than for low-income households.

From First-Order Condition (3), $f' > 0$, and $g'' < 0$, it also follows that *ceteris paribus* households that are attentive to electricity consumption issues ($a_i = 1$) consume less electricity than inattentive households ($a_i = 0$): $e_i^1 < e_i^0$, where e_i^1 and e_i^0 denote the respective household consumption levels. For example, assuming that well-educated households are more attentive to energy issues than low-educated households, all else equal, we would expect well-educated households to exhibit a lower electricity consumption than low-educated households.

Similarly, we would assume that with respect to energy issues, homeowners are more attentive than tenant households and thus tend to have a lower electricity use than tenants. These assumptions are supported by our empirical data, which indicate that the annual electricity consumption per square meter is about 7.4% lower for homeowners than for tenants, a difference that is non-vanishing also in statistical terms ($t = 12.57$). Likewise, the electricity consumption per square meter of households whose head has a college degree is 8.0% lower than for other households ($t = 12.46$).

To theoretically analyze the heterogeneity in the demand response to price changes with respect to attentiveness, we compare the derivative given by Equation (5) for attentive households,

$$\frac{\partial e_i}{\partial p} \Big|_{a_i=0} = - \frac{e_i^0 f''(m - p e_i^0)}{g''(e_i^0) + p f''(m - p e_i^0)}, \quad (7)$$

with that for inattentive households:

$$\frac{\partial e_i}{\partial p} \Big|_{a_i=1} = - \frac{e_i^1 f''(m - p e_i^1)}{g''(e_i^1) + p f''(m - p e_i^1) - h''(e_i^1)}. \quad (8)$$

It remains unclear, though, whether $\frac{\partial e_i}{\partial p} \Big|_{a_i=1}$ is larger in magnitude than $\frac{\partial e_i}{\partial p} \Big|_{a_i=0}$, as

these derivatives differ in two competing factors that affect the magnitude of the price reaction in an opposing way, where the effect of attentiveness on the price response is moderated by the difference in the electricity consumption level: $e_i^0 > e_i^1$. Again, we therefore conclude that the demand response to price changes with respect to attentiveness is an empirical issue that will be addressed in the penultimate section, in which we investigate the heterogeneity in the electricity demand response to price changes across various household groups, such as homeowner versus tenants. These groups can be expected to differ with respect to numerous characteristics, not least their attention to electricity issues.

3 Data

Our empirical research on electricity demand responses to price changes draws on a large household panel data set originating from 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) – for more information on the GRECS, see www.rwi-essen.de/GRECS. The survey data was jointly gathered by RWI and the professional survey institute *forsa*, using *forsa's* household panel that is representative for the German population aged 14 and above – for more information, see www.forsa.com.

In five surveys spanning the period 2006 to 2014, each among 6,500 to 8,500 households, participants – the household heads in this case – reported information on their household's electricity consumption, prices, and costs. This information is drawn from the households' electricity bills that cover the years prior to each survey year. In the best case, a household head reported electricity information for up to $T = 9$ years. While this was the case for only 3 households, about 60% of the respondents reported electricity information at least twice (see Table A1 in the appendix). Respondents also provided numerous details on socio-economic and other household characteristics, such as household size, household net income, age, education, as well as location and

ownership of the household's residence.

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. *forsa's* survey tool allows respondents to complete the questionnaire either online or, if internet access is not available, using a television. Respondents can interrupt and continue the survey at any time.

The billing information includes marginal prices per kWh, monthly fixed fees, total electricity expenditures, and consumption levels for the billing period. In the frequent case that a bill does not cover the entire calendar year, we have extrapolated the annual consumption on the basis of the mean consumption per day for the period for which information is available. To exclude seasonal impacts, we only use information from electricity bills with a duration of more than 180 days. Owing to possible typing errors, we clean the data set via an iterative process that, separated by household size, drops observations whose consumption figure and average price do not lie in intervals that span two standard deviations around the respective means. Despite this loss of observations, our analysis benefits from an abundant database: Overall, our estimation sample consists of 24,336 valid observations on electricity consumption levels and prices originating from 10,915 households, implying a mean number of 2.23 observations per household (see Table A1 in the appendix).¹

Given the high share of 31% of respondents with a college degree in our sample (Table 1), the database is not representative for German households (see Table A2 in the appendix). This conclusion is further substantiated by the fact that single-person households are less prevalent in our sample than in the population of German house-

¹Households with night storage heating systems, which represent a small minority of about 3% of the German household population (RWI and *forsa*, 2015), have been excluded from our sample, as their electricity consumption is substantially above average and they enjoy a separate low tariff for heating purposes.

holds. Not least, about one third of them are female and, thus, women are considerably less frequent in the sample than men. This fact is a consequence of our decision to ask only household heads to participate in the survey, as, by definition, they typically make financial decisions at the household level and are more likely to report billing data.

Table 1: Descriptive Statistics for the Estimation Sample

Variable	Explanation	Mean	Std. Dev.
Age	Age of respondent	52.66	13.27
College degree	Dummy: 1 if respondent has college degree	0.310	-
Female	Dummy: 1 if female household head	0.321	-
Household size = 1	Dummy: 1 if household comprises one member	0.213	-
Household size = 2	Dummy: 1 if household comprises two members	0.446	-
Household size = 3	Dummy: 1 if household comprises three members	0.163	-
Household size = 4	Dummy: 1 if household comprises four members	0.131	-
Household size > 4	Dummy: 1 if household comprises five or more members	0.047	-
Homeowner	Dummy: 1 if household lives in an own dwelling	0.647	-
East Germany	Dummy: 1 if household resides in East Germany	0.204	-
Income	Monthly net household income in €	2,748	1,181
Consumption y	Annual electricity consumption in kWh	3,487	1,673
p	Average electricity price in cent per kWh	24.52	4.28
z	Sum of fees, taxes, and levies in cent per kWh	11.89	2.23

Note: Number of observations and households employed for estimations: 24,336 and 10,915, respectively. Income information was provided in €500 intervals, from which a continuous variable has been derived by assigning the mid-point of the interval reported.

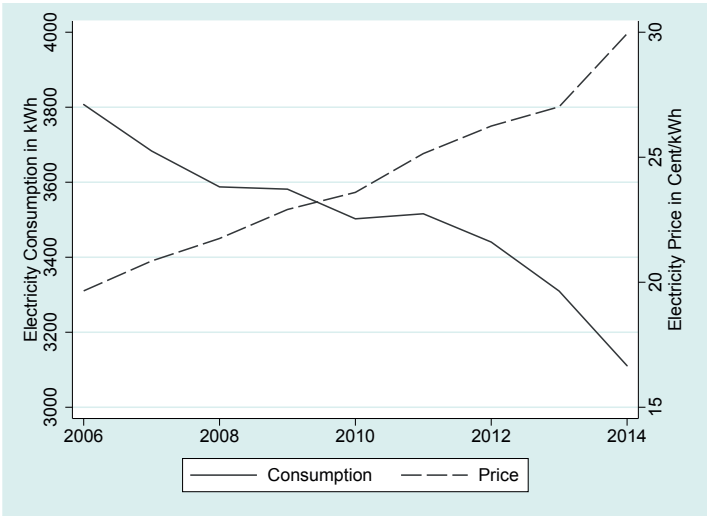
As marginal prices are much less frequently reported from the household heads than expenditure and consumption figures, the key variable employed in our analysis is the average electricity price, calculated by dividing electricity expenditures by consumption figures. The choice of the average, rather than the marginal price, however, has hardly any bearing on our key results and conclusions: In qualitative terms, using marginal, rather than average prices yields similar estimation results (see Table A5 in the appendix). Moreover, although a central assumption in economic theory is that consumers optimize with respect to marginal prices, recent empirical findings suggest that consumers tend to react to average prices because of limited attention to complex pricing schedules (Borenstein, 2009; Ito, 2014).

The average price is clearly an endogenous measure, as, by definition, it is a function of electricity consumption, the dependent variable of our analysis. Yet, endogeneity problems afflict both average and marginal prices, as nowadays German consumers are free to choose from a broad range of electricity tariffs. Since the liberal-

ization of Germany’s electricity market in 1998, changing both suppliers and tariffs is a common phenomenon. Therefore, a simultaneity problem may arise (Taylor et al., 2004): on the one hand, consumption levels tend to be affected by prices, but, on the other hand, households’ tariff selection may depend on consumption levels.

Figure 1 provides a first notion on the relationship between average household prices and their annual electricity consumption in the survey period 2006-2014. Mean annual electricity consumption decreased from 3,807 kWh in 2006 to 3,111 kWh in 2014, whereas mean electricity prices rose from 19.7 to 29.9 cents per kWh in the same period. Using these values, a first reference point for our price elasticity estimates presented in Section 5 can be obtained by dividing the relative consumption decrease by the percentage price increase. This back-of-the-envelope calculation yields a crude estimate of the long-run price elasticity of -0.49 for the period 2006 to 2014.

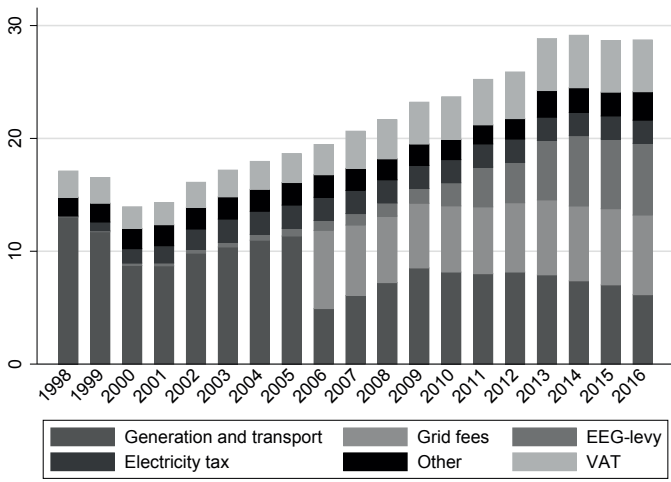
Figure 1: Mean Household Electricity Consumption per Year and Average Household Electricity Prices in Cents per kWh (Source: German Residential Energy Consumption Survey (GRECS)).



The average prices resulting from the sample closely match the means that are reported by the German Association of Energy and Water Industries (BDEW) for households consuming 3,500 kWh per year (Figure 2). According to BDEW (2017), for this household type, the mean electricity price more than doubled between 2000 and 2016,

rising from 13.94 to 28.69 cents per kWh. Fees, levies, and taxes, introduced and increased by the German government over time, are blamed to be major drivers of this sharp increase (BDEW, 2017). For instance, the so-called EEG levy for the promotion of renewable technologies, which was introduced in 2000 at the level of 0.3 cents per kWh, skyrocketed to 6.35 cents in 2016 and, including value-added tax, accounted for about a quarter of the household electricity price reported by BDEW (2017).

Figure 2: Composition of Household Electricity Prices for a Household with an Annual Consumption of 3,500 kWh (Source: BDEW, 2017).



Another substantial electricity price component are grid fees, which have strongly increased over time and vary substantially across regions. Grid fees are raised to cover maintenance costs, as well as the costs that grid operators incur when connecting consumers and new power plants to the grid. As grid operators are regional monopolies, they are regulated by the federal grid agency (Bundesnetzagentur, BNetzA) and allowed to pass on their costs to the customers. Currently, there are 884 grid operators in Germany (BNetzA, 2017), which operate in regions that typically cover multiple zip codes.

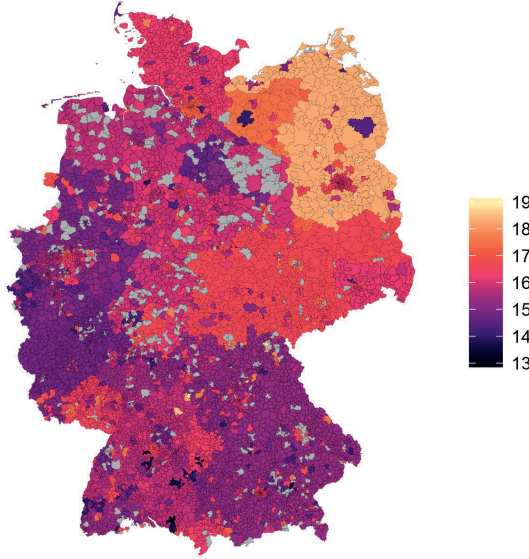
As instrumental variable z for the endogenous average price p , following Frondel and Kussel (2019) we employ the sum of regulated price components. These consist

of grid and concession fees, levies, and taxes, such as the German eco-tax, a tax on electricity use of 2.05 cents per kWh. Hence, except for generation and transport cost, instrumental variable z comprises all elements illustrated by Figure 2. While some price components only exhibit temporal variation because they apply to all household customers in Germany alike, such as the eco-tax, other price components vary notably across both time and regions, in particular grid fees. This sum of the regulated price components averaged 11.9 cents per kWh over the period 2006-2014 and remained relatively stable around 10 cents per kWh between 2006 and 2010, but then rose up to 15 cents by 2014. This increase was mainly caused by a strong deployment of renewable energy installations that resulted in both a higher EEG levy and higher grid fees due to costs for connecting new installations (Andor et al., 2017).

Figure 3 illustrates that the regulated price components as captured by instrument z exhibit strong regional variation, both across but also within federal states. Varying between 12.7 and 19.1 cents per kWh in 2014, z is higher in East and North Germany than in South Germany, most notably because of a relatively high deployment of windmills. In these regions, between 2006 and 2014, the increase in the grid fees, a major component of z , was notably stronger than in other parts of Germany. Figure A1, presented in the appendix, illustrates a similarly strong regional variation in our instrument z for the year 2006, ranging from 7.7 to 13.0 cents per kWh. In addition, a comparison of both figures reveals that z is substantially lower for 2006 than for 2014.

With a correlation coefficient of $\rho = 0.68$ that reflects the expected positive correlation between the average price p and instrument z , there is evidence that the first assumption for the validity of instrumental variables holds: $Cov(p, z) \neq 0$. Moreover, while grid fees are regional-specific and taxes and levies are uniform for all households, the sum of these price components is the same for all households of a certain region and is exogenous to households. Thus, it is highly warranted to assume that our instrument z satisfies the second identification assumption for valid instruments: $Cov(z, \nu) = 0$, that is, z is uncorrelated with the error term ν of the regression equation.

Figure 3: Regional Variation of the Regulated Electricity Price Components (Grid Fees, Levies, and the German Eco-Tax) in Germany in 2014.



4 Methodology

To provide for a reference point for the results obtained from employing dynamic panel estimation methods, we first use a static model and estimate the double-log specification that is typically employed for the estimation of demand elasticities:

$$\ln y_{it} = \beta + \beta_p \ln p_{it} + \beta_x^T \mathbf{x}_{it} + \tau_t + \mu_i + v_{it}, \quad (9)$$

where y_{it} refers to the electricity demand of household i in year t , p_{it} denotes the average electricity price that household i had to pay in t , vector \mathbf{x} comprises household characteristics, and β_x is the corresponding parameter vector. β_p is the coefficient of interest that reflects the demand elasticity with respect to prices, τ_t and μ_i are year- and individual fixed effects, respectively, and v_{it} designates the idiosyncratic error term.

To cope with the likely endogeneity of prices p , we pursue a panel IV approach and employ the sum of regulated price components as instrumental variable z , thereby

following the suggestion of McFadden et al. (1977), who argue that components of the total price are a natural set of instruments. Employing the common two-stage procedure (2SLS), in the first stage of our IV approach, we regress the logged average price p on the log of instrument z , as well as the set of household characteristics \mathbf{x} :

$$\ln p_{it} = \gamma + \gamma_z \ln z_{it} + \gamma_{\mathbf{x}}^T \mathbf{x}_{it} + \tau_t + \mu_i + u_{it}. \quad (10)$$

In the second stage, the price prediction \hat{p} obtained from Equation (10), rather than the actual price p , is employed to estimate Equation (9).

The static model given by Equation (9) assumes that households instantaneously adjust their utilization behavior and their appliance stock as a response to varying electricity prices. Implying that short- and long-run elasticities are identical (Alberini and Filippini, 2011), this is a heroic assumption, given that electric appliances have long life cycles and households often have to incur substantial costs to adapt their appliance stock.

To account for sluggish appliance stock adjustments and, hence, utilization behavior that is rather inflexible in the short run, the lagged value $y_{i,t-1}$ of the dependent variable is included among the regressors, being characteristic for dynamic panel data models:

$$\ln y_{it} = \beta + \beta_y \ln y_{i,t-1} + \beta_p \ln p_{it} + \beta_{\mathbf{x}}^T \mathbf{x}_{it} + \tau_t + \mu_i + v_{it}, \quad (11)$$

with v_{it} designating another idiosyncratic error term and β_y denoting the coefficient on the lagged dependent variable. Dynamic panel data models are characterized by two sources of persistence over time: Autocorrelation due to the presence of a lagged dependent variable among the regressors and individual effects μ_i reflecting the heterogeneity among individuals.

Estimating dynamic Model (11) on the basis of OLS methods yields inconsistent estimates, as the individual effect μ_i enters all values of the dependent variable y , implying that the lagged dependent variable cannot be independent of the composite error process $\mu_i + v_{it}$. For the same reason, estimating Equation (11) using random-

effects estimation methods yields inconsistent estimates as well.

Moreover, when Equation (11) is estimated using fixed-effects methods, the resulting estimates suffer from the Nickell bias, particularly in short panels (Nickell, 1981), that is, for small T (see e. g. Baltagi, 2005, p.136f.). As Nickell (1981) demonstrates, this bias arises because the within transformation that is typically employed for fixed-effects estimations creates a correlation between the regressors and the error term. Note therefore that the Nickell bias is not due to an autocorrelated error process, but arises even if the error terms v_{it} were to be independent and identically distributed.

One alternative to consistently estimate Equation (11) involves taking first differences of the original Model (9) to eliminate the problems arising from the individual effects μ_i :

$$\Delta \ln y_{it} = \beta_y \Delta \ln y_{i,t-1} + \beta_p \Delta \ln p_{it} + \beta_x^T \Delta \mathbf{x}_{it} + \Delta \tau_t + \Delta \epsilon_{it}, \quad (12)$$

and to use either $\Delta y_{i,t-2} := y_{i,t-2} - y_{i,t-3}$ or $y_{i,t-2}$ as an instrument for $\Delta y_{i,t-1} := y_{i,t-1} - y_{i,t-2}$ (Anderson and Hsiao, 1982). These instruments will not be correlated with $\Delta v_{it} := v_{it} - v_{i,t-1}$ as long as the error terms v_{it} are not serially correlated (Baltagi, 2005, p.136f.).

Yet, Arellano and Bond (1991) argue that, albeit consistent, this estimator is not necessarily efficient, because it does not make use of all the available moment conditions. Instead, they advocate for employing what is now frequently called the Arellano-Bond difference GMM estimator, which uses the generalized method of moments (GMM) and exploits all orthogonality conditions between the lagged values of y_{it} and the error term v_{it} (Blundell and Bond, 1998, p.118): $E(y_{i,t-s} \Delta v_{it}) = 0$ for $t = 3, \dots, T$ and $s \geq 2$. For instance, for $T = 3$, y_{i1} is a valid instrument for Δy_{i2} , since it is highly correlated with $y_{i2} - y_{i1}$, but uncorrelated with $(v_{i3} - v_{i2})$ as long as the error terms are not serially correlated. Next, for $T = 4$, both y_{i1} and y_{i2} are valid instruments for $\Delta y_{i4} := y_{i4} - y_{i3}$. One can continue in this fashion, adding an extra valid instrument for each forward period, so that the set of valid instruments becomes $y_{i1}, y_{i2}, \dots, y_{i,T-2}$ for any period T .

According to Blundell and Bond (1998), however, the Arellano-Bond estimator can have a large finite sample bias and poor precision, because lagged levels of y_{it} are weak instruments for first differences. Building upon Arellano and Bover (1995), Blundell and Bond (1998) develop a system GMM estimator that uses both lagged differences of y_{it} to instrument for levels and lagged levels of y_{it} as instruments for differences. This results in a (stacked) system of $T - 2$ equations in first differences as well as $T - 2$ equations in levels, as for the periods $3, \dots, T$, valid instruments are available. Hence, the Blundell-Bond estimator builds on a system of two sets of equations: the original equation and that in first differences. In short, Blundell and Bond (1998) augment the Arellano-Bond estimator by invoking the additional assumption that first differences of instrument variables are uncorrelated with the fixed effects, which allows the introduction of more instruments and can dramatically improve efficiency.

To deal with gaps in unbalanced panels, we follow Arellano and Bover's (1995) suggestion and use forward orthogonal deviations, that is, the average of all future available observations of a variable. Furthermore, following Roodman (2009a), we use all valid lags of the untransformed variables as instruments, but limit the number of instruments employed to prevent over-fitting.

5 Empirical Results

Presenting the estimation results of various model specifications and estimators, this section serves to demonstrate how model design and the choice of the estimation method may vary price elasticity estimates. Common to all specifications is the set of socioeconomic characteristics, as well as the inclusion of year and federal state dummies to capture differences in weather, geography, etc.

5.1 Results from the Static Model

Using the results originating from static Model (9) as a reference case for the outcomes obtained from dynamic Model (11), we first report the OLS estimates (Table 2).

Ignoring the endogeneity of average prices and failing to account for individual effects μ_i yields an OLS estimate of the price elasticity that exceeds minus one, a magnitude that is well-known from the literature (Taylor et al., 2004). Taking the endogeneity of the electricity price into account by using the sum of regulated price components as an instrument, the 2SLS estimation provides for a price elasticity estimate of about -0.64, which is much lower in magnitude than the OLS estimate.

There is empirical evidence on the strength of our instrument: Given a correlation coefficient of $\rho = 0.68$, instrument z exhibits a strongly positive correlation with price variable p , a fact that is confirmed by the first-stage estimation results presented in Table A3 in the appendix, where the coefficient estimate for instrument z is positive and statistically different from zero at the 1% significance level. To further gauge the strength of our instrument, we employ the rule of thumb of Staiger and Stock (1997), according to which the F statistic for the coefficient γ_z of First-Stage Regression (10) should exceed the threshold of 10 (Murray, 2006). With an F statistic of $F(1; 18, 992) = 237.2$ resulting from the first-stage estimation of the static 2SLS model, we can reject the null hypothesis that the second-stage equation is weakly identified.

Table 2: Estimation Results for Static Model (9) on Electricity Demand based on various Estimation Methods.

	Non-Panel Methods				Panel Methods			
	OLS		2SLS		Fixed Effects		Fixed Effects 2SLS	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
$\ln(p)$	-1.403***	(0.024)	-	-	-0.486***	(0.026)	-	-
$\ln(\widehat{p})$	-	-	-0.639***	(0.203)	-	-	0.076	(0.288)
$\ln(\text{Income})$	0.064***	(0.005)	0.076***	(0.006)	0.000	(0.012)	-0.006	(0.013)
Household size = 2	0.355***	(0.007)	0.414***	(0.017)	0.225***	(0.023)	0.261***	(0.033)
Household size = 3	0.571***	(0.008)	0.652***	(0.023)	0.347***	(0.025)	0.390***	(0.037)
Household size = 4	0.661***	(0.009)	0.752***	(0.027)	0.414***	(0.027)	0.449***	(0.040)
Household size > 4	0.833***	(0.013)	0.922***	(0.029)	0.437***	(0.043)	0.486***	(0.054)
College degree	-0.028***	(0.005)	-0.032***	(0.006)	0.009	(0.015)	0.006	(0.016)
Age	0.004***	(0.000)	0.005***	(0.000)	0.002	(0.002)	0.002	(0.002)
Female	-0.001	(0.005)	-0.006	(0.005)	-0.004	(0.019)	0.003	(0.018)
Homeowner	0.137***	(0.005)	0.152***	(0.007)	0.128***	(0.031)	0.144***	(0.036)
Constant	11.091***	(0.089)	8.642***	(0.648)	9.107***	(0.165)	7.424***	(0.886)
Year Dummies	Yes		Yes		Yes		Yes	
State Dummies	Yes		Yes		Yes		Yes	
Number of observations	21,918		19,026		21,918		19,026	

Note: Standard errors are clustered at the individual level. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

Upon exploiting the panel structure of our data and comparing the fixed-effects with the random-effects results, based on a Hausman (1978) specification test, the null hypothesis of equal sets of coefficient estimates can be rejected, suggesting that the fixed-effects results should be preferred. Accordingly, we report the fixed-effects estimation results in Table 2, while the random-effects estimates are presented in Table A4 of the appendix, the latter being generally larger in magnitude than the fixed-effects estimates. Specifically, the short-run price elasticity estimate of about -0.71 originating from the random-effects estimation is higher in magnitude than the fixed-effects estimate of about -0.49.

By additionally instrumenting price variable p to address endogeneity issues, the resulting 2SLS fixed-effects estimate of the short-run price elasticity is not significantly different from zero in statistical terms. For the remaining covariates, such as household size and income, coefficient estimates do not vary much across estimation methods. For instance, based on the fixed-effects 2SLS estimates, the average electricity consumption of a household with two members is about $100[\exp(0.261) - 1] = 30\%$ higher than that of a single-person household. Likewise, homeowners tend to have a higher consumption than other households.

5.2 Results from the Dynamic Model

As static models fail to account for sluggish adjustments of the appliance stock, we continue by reporting the estimates from dynamic Model (11), in which lagged electricity consumption is included as an additional variable to control for such adjustments. Referring to the 2SLS estimates, the short-run price elasticity of demand amounts to about -0.23 (Table 3), an estimate that is substantially lower in magnitude than the static price elasticity estimate of about -0.64 reported in Table 2. The small magnitude of the short-run price elasticity is due to the fact that in dynamic Model (11), the price variable merely captures short-run changes in utilization behavior, but not any long-run adjustment.

Using the estimate of 0.864 of the coefficient β_y on the lagged consumption variable, the long-run price elasticity can be computed by dividing the short-run price elasticity estimate of -0.229 by $1 - \beta_y$: $\beta_p / (1 - \beta_y) = -0.229 / (1 - 0.864) = -1.684$. The corresponding standard error of 0.820 is computed using the delta method (Greene, 2003, p. 68). Accounting for the panel character of our data by using fixed-effects estimation methods yields a long-run elasticity that is close to zero. Interestingly, the coefficient on the lagged consumption term drops to 0.188. While the 2SLS estimate is biased upward because of the correlation between the lagged consumption term and the fixed effects, in contrast, fixed-effects estimates are downward biased. Hence, the true value must lie in the interval spanned by the 2SLS and the fixed-effects estimates (Roodman, 2009b).

Table 3: Estimation Results for Dynamic Model (11) on Electricity Demand based on various Estimation Methods.

	2SLS		Fixed-Effects 2SLS		Blundell-Bond	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
$\ln(\widehat{p})$	-0.229*	(0.137)	-0.093	(0.325)	-0.444*	(0.236)
$\ln(y_{t-1})$	0.864***	(0.016)	0.188***	(0.039)	0.330***	(0.104)
$\ln(\text{Income})$	0.002	(0.004)	0.003	(0.017)	0.042***	(0.011)
Household size = 2	0.063***	(0.007)	0.251***	(0.049)	0.292***	(0.047)
Household size = 3	0.094***	(0.009)	0.392***	(0.056)	0.455***	(0.072)
Household size = 4	0.103***	(0.009)	0.431***	(0.056)	0.514***	(0.082)
Household size >4	0.126***	(0.010)	0.407***	(0.074)	0.624***	(0.101)
College degree	-0.002	(0.004)	0.008	(0.019)	-0.018**	(0.008)
Age	-0.000	(0.000)	0.003	(0.002)	0.003***	(0.001)
Female	-0.002	(0.003)	0.017	(0.022)	-0.003	(0.007)
Homeowner	0.015***	(0.004)	0.041	(0.036)	0.095***	(0.018)
Constant	1.728***	(0.590)	6.328***	(1.233)	6.002***	(1.204)
Year Dummies		Yes		Yes		Yes
State Dummies		Yes		Yes		Yes
Number of observations		8,096		8,096		8,096
Number of instruments		-		-		40
Arellano-Bond test for AR(1)		-		-		$z = -4.48$; $p = 0.000$
Arellano-Bond test for AR(2)		-		-		$z = 1.15$; $p = 0.249$
Hansen test of overid. restrictions		-		-		$\chi^2(6) = 4.22$; $p = 0.647$
Long-run price elasticity	-1.684***	(0.820)	-0.115	(0.398)	-0.663**	(0.338)

Note: Standard errors are clustered at the individual level. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level respectively. Standard errors for the long-run elasticities are computed using the delta method.

Given that in a dynamic setting fixed-effects estimation methods suffer from Nickell bias, we finally present the results originating from the Blundell-Bond GMM system

estimator.² By employing the differences of the dependent variable as instruments for levels and lagged levels of the dependent variable as instruments for differences, the correlation between the lagged consumption term and the fixed effects are eliminated (Roodman, 2009b). It bears noting that, as to be expected, the coefficient on the lagged consumption term lies between the 2SLS and the fixed-effects 2SLS estimates. Both the coefficient estimates on the price variable and lagged consumption are statistically different from zero, resulting in short- and long-run elasticity estimates of -0.44 and -0.66, respectively. The long-run elasticity of -0.66 is in line with the few other estimates that are available for Germany: Based on expenditure rather than consumption data, Nikodinoska and Schröder (2016) and Schulte and Heindl (2017) find long-run elasticities of -0.81 and -0.43, respectively.

Statistical tests indicate the validity of the Blundell-Bond estimates, with the results benefitting from the large number of 8,096 observations that are available for the estimations. Relative to this large data base, the number of 40 instruments is low. Arellano and Bond (1991) proposed a test for the null hypothesis that there is no second-order serial correlation for the disturbances of a first-differenced model, such as Model (12). This test is important because the consistency of the GMM estimator relies upon the assumption that $E[\Delta v_{it} \Delta v_{i,t-2}] = 0$. The p-value of 0.249 reported in Table 3 indicates that the test statistic for the AR(2) test on the lack of second-order correlation in the first-differenced residuals is not different from zero in statistical terms, providing evidence that it would not be appropriate to include a second-order lag of the dependent variable in Model (12). In contrast, the corresponding statistic for the AR(1) test hints to the appropriateness of including a first-order lag of the dependent variable as a regressor in Model (12). Finally, the Hansen test on overidentifying restrictions indicates that the null hypothesis of the joint validity of the instruments cannot be rejected. This test not only shows that our set of instruments is valid, but also that the model is

²To this end, the Stata command `xtabond2` written by Roodman (2009a) has been employed. Table A6 of the appendix presents robustness checks in which we vary the way in which the endogenous lagged variable is instrumented. The long-run price elasticity estimates originating from these estimation variants are somewhat larger, but the differences across variants are not significantly different from zero in statistical terms.

correctly specified (Roodman, 2009b).

6 Heterogeneous Effects

Building upon our preferred estimation method, the Blundell-Bond estimator, and exploiting the socioeconomic characteristics recorded in our data set, we now investigate the heterogeneity in demand responses to changing electricity prices by separately estimating dynamic Model (12) for various types of households. Despite the extensive empirical evidence on electricity price elasticities received from the literature, there are only a few studies that compare price elasticities across socioeconomic groups, with previous studies concentrating on the role of income (e.g. Reiss and White, 2005; Schulte and Heindl, 2017; Silva et al., 2017).

Beginning our heterogeneity analysis by distinguishing between low- and high-income households, defined here by a monthly household net income below €1,250 and above €3,500, respectively, the estimation results suggest that the price responsiveness of high-income households is substantially higher than that of other households, with short- and long-run price elasticity estimates amounting to -0.86 and -1.29, respectively (Table 4).³ Being in line with the results of Schulte and Heindl (2017) and Nikodinoska and Schröder (2016), the finding that high-income households are highly responsive to price changes may reflect the rationale that wealthy households tend to exhibit a preference for more energy-efficient appliances (Alberini et al., 2011) and are more capable of adjusting their appliance stock towards less electricity-intensive equipment as a response to rising electricity prices (Spees and Lave, 2007). We can lend support to the conjecture that high-income households own less electricity-intensive appliances by merging our data set with detailed appliance stock data that we gath-

³Note that the confidence intervals reported in Table 4 for the long-run price elasticity estimates overlap for all comparisons, such as that between low- and high-income groups. Only the point estimate of -0.41 for tenants falls outside the confidence interval pertaining to the homeowners, indicating that the price response for tenants is statistically different from that of homeowners. Apart from this exception, though, all other comparisons do not indicate significant differences of the price elasticity estimates in statistical terms. Nonetheless, based on all the strong differences in the point estimates, we interpret our findings as tentative evidence for different demand responses.

ered for a subset of our sample (see Frondel et al., 2017 for a description of the data set). On this empirical basis, we find that high-income households are more likely to hold new, and thus more energy-efficient, appliances, in particular freezers and dishwashers (see Table A7 of the appendix).

Table 4: Heterogeneous Electricity Demand Responses to Price Changes across various Household Groups based on the Blundell-Bond estimation of Dynamic Model (12)

	$\widehat{\ln(p)}$		$\ln(y_{t-1})$		Long-run Price Elasticity			Number of Observations
	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	95% CI	
Low-income household	-0.424	(0.628)	0.251	(0.413)	-0.57	(0.887)	[-2.30,1.17]	1,232
High-income household	-0.855**	(0.352)	0.336*	(0.155)	-1.29***	(0.477)	[-2.22,-0.35]	2,215
Tenant	-0.281	(0.418)	0.311	(0.259)	-0.41	(0.593)	[-1.57,0.75]	2,899
Homeowner	-0.715***	(0.210)	0.337***	(0.103)	-1.08***	(0.278)	[-1.62,-0.53]	5,197
Male household head	-0.606**	(0.236)	0.356**	(0.103)	-0.94**	(0.212)	[-1.63,-0.25]	5,606
Female household head	-0.259	(0.219)	0.251	(0.193)	-0.34	(0.279)	[-0.89,0.20]	2,490
No college degree	-0.334	(0.296)	0.210	(0.133)	-0.42	(0.367)	[-1.14,0.297]	5,552
College degree	-0.645**	(0.279)	0.499**	(0.130)	-1.29**	(0.508)	[-2.28,-0.29]	2,554
Low consumption	-0.245	(0.237)	0.062	(0.156)	-0.26	(0.253)	[-0.757,0.234]	3,933
High consumption	-0.416	(0.267)	0.277***	(0.100)	-0.58	(0.360)	[-1.282,0.131]	4,163

Note: Standard errors are clustered at the household level. ***,**, and * denote statistical significance at the 1 %, 5 %, and 10 % level respectively. Standard errors for the long-run elasticities are computed using the delta method. All models include socioeconomic characteristics, as well as year and state dummies.

We next split the sample into homeowners and tenants, motivated by the expectation that homeowners are more attentive to electricity issues than tenants, finding strong and statistically significant price responses for homeowners, yet not for tenants. In addition to differences in attentiveness, this divergent result might be rooted in the landlord-tenant dilemma (Allcott and Greenstone, 2012): If landlords bear the tenants' cost of electricity consumption, tenants have little incentive to use electricity efficiently (Levinson and Niemann, 2004) and, hence, exhibit a low price elasticity. Conversely, if tenants have to pay for the electricity costs, landlords do not have an incentive to equip rental apartments with energy-efficient appliances, resulting in a low demand response among tenants as well. These incentives might explain Davis' (2011) finding that tenants are less likely to have energy-efficient appliances, a finding that is not confirmed by our data, though (Table A7).

With respect to gender differences, the psychological literature indicates that women have less experience with issues related to electricity (Chambers and Andre, 1997), a circumstance that might translate into a lower degree of price responsiveness via var-

ious channels, such as a lacking knowledge of consumption levels and prices. This argument is in line with Frondel and Kussel (2019) and Jessoe and Rapson (2014), who provide evidence that only those households heads who are informed about electricity prices react to price changes.

Our results corroborate these studies: exploiting information gathered in two out of four survey waves, in which we asked participants to guess their individual electricity prices prior to requesting their billing data, we find that the share of women who provide such a guess is almost 25 percentage points lower than the respective share for men. As indicated by the t statistic of $t = 36.48$, the difference in these shares is significant in statistical terms. Furthermore, our data suggest that, on average, men are nearly 5 percentage points more likely to report valid billing information than women ($t = 11.81$), presumably reflecting a higher availability of billing data due to a stronger interest in electricity consumption issues. Both empirical results may be indications of a higher attentiveness to electricity issues, potentially leading to a higher price responsiveness among households with a male head than for those with a female head (Table 4).

The same line of reasoning may apply to respondents with higher education, as education may be positively correlated with attentiveness and price knowledge. In fact, our data indicates that the likelihood to provide a guess of the electricity price is about 5 percentage points higher among college graduates than among other individuals ($t = 5.69$). This evidence on a better price knowledge of high-educated individuals may explain our finding that households whose head has a college degree strongly react to prices, whereas there is no price reaction among household heads without a college degree (Table 4).

Lastly, splitting our observations at the median electricity consumption, we analyze the heterogeneity in price responses with respect to the consumption level. As a result, with -0.58 , the elasticity estimate is twice as large in magnitude for households with high electricity consumption levels than that for the low-consumption group. Albeit both estimates are statistically indistinguishable at conventional significance

levels, our results contrast with those of Reiss and White (2005), who show that price elasticities are lower in magnitude for consumers with high consumption levels.

7 Summary and Conclusions

The residential sector accounts for a substantial share of electricity demand in industrialized countries, being responsible for about a quarter of Germany's total electricity consumption (AGEB, 2016). Strengthening incentives to reduce household electricity demand, such as raising a carbon tax, thus appears to be a promising avenue to reach climate policy targets by diminishing the residential sector's greenhouse gas emissions. One has to bear in mind, though, that any endeavor to conserve electricity via increasing taxes may have substantially adverse regressive effects for low-income households (Frondel et al., 2015; Heindl and Schüssler, 2015). From a social policy perspective, it is therefore advisable that any such endeavor is accompanied by support schemes to alleviate the resulting burden for poor households. The effectiveness of such price measures, however, critically hinges on the response of household demand to price increases.

Drawing on household panel data from the German Residential Energy Consumption Survey (GRECS) that span over nine years (2006-2014), this paper has estimated the response of household electricity demand to price changes using the composite of regulated price components, including the levy raised for the promotion of renewable technologies, as an instrument to cope with the likely endogeneity of electricity prices. A distinguishing feature of our study is that we empirically investigate the heterogeneity in demand responses across households types to provide an informed, yet so far unavailable, basis for evaluating the effectiveness of price policies to reduce electricity consumption as a means to combat climate change. Inspired by concepts of behavioral economics, we have established a theoretical model in which attention to electricity consumption issues plays a key role in explaining heterogeneity in electricity demand across households. Ultimately, though, we argue that the analysis of

demand responses to price changes across household groups remains an empirical issue.

By comparing the results obtained from a dynamic model based on the GMM system estimator developed by Blundell and Bond (1998) with those resulting from standard panel methods and a classic instrumental variable approach, we have demonstrated that price elasticity estimates may be biased if the methodological challenges resulting from the particularities of the residential demand for electricity are not adequately addressed.

On the basis of the Blundell-Bond estimator for dynamic panel models, we find short- and long-run price elasticity estimates of -0.44 and -0.66, respectively. These results suggest that, at least in the long run, reductions in the residential electricity demand can be triggered by increasing prices, for instance by raising Germany's eco-tax on electricity use introduced in 1999. Moreover, exploiting the abundance of our data set by estimating dynamic models for various types of households individually, a distinguishing feature of our study is the finding of a large heterogeneity in household responses. According to our results, in contrast to wealthy households and homeowners, low-income households, tenants, and women do not adjust their electricity demand as a response to increasing prices. These results suggest that increasing electricity prices, for instance via raising a carbon tax, may not be a universally effective means.

The absence of any price responses among certain household groups, such as low-income households, has important implications for energy conservation programs, calling for additional non-pricing measures to reduce the greenhouse gas emissions originating from fossil-based electricity generation. For instance, non-pricing measures, such as energy audits, information campaigns and subsidies for the purchase of energy efficient appliances (Allcott et al., 2015; Fowlie et al., 2015), should be included in energy conservation programs to target household groups that do not seem to respond to price increases, such as low-income households. Targeted programs that address these groups may ensure a more effective usage of resources than unspecific

programs.

Appendix

Table A1: Frequency in the GRECS Survey Participation of Households and Number of Observations

Number of Responses	Frequency	Share	Cumulated	Number of Observations
1	4,421	40.5 %	40.5 %	4,421
2	3,100	28.4 %	68.9 %	6,200
3	1,682	15.4 %	84.3 %	5,046
4	727	6.7 %	91.0 %	2,908
5	486	4.4 %	95.4 %	2,403
6	235	2.2 %	97.6 %	1,410
7	194	1.8 %	99.4 %	1,358
8	67	0.57 %	99.97 %	536
9	3	0.03 %	100.0 %	27
Total	10,915	100.0 %	–	24,336

Table A2: Comparison of our Estimation Sample with the Population of German Households

Variable	2006			2014		
	Sample	Population	t Statistics	Sample	Population	t Statistics
Age under 25 years	3.1%	5.0%	-4.15***	0.4%	4.7%	-42.17***
Age 25 – 64 years	83.9%	67.7%	16.78***	67.6%	67.0%	0.76
Age 65 years and more	13.0%	27.2%	-16.09***	32.0%	28.1%	4.99***
College degree	34.0%	15.7%	14.68***	35.5%	19.0%	20.39***
Female	32.6%	34.1%	-1.22	31.2%	35.4%	-5.32***
Household size = 1	19.6%	38.8%	18.38***	22.7%	40.8%	-25.63***
Household size = 2	39.4%	33.6%	4.54***	53.2%	34.4%	22.33***
Household size = 3	18.2%	13.5%	4.60***	12.0%	12.4%	-0.77
Household size = 4	16.7%	10.3%	6.54***	9.1%	9.1%	-0.06
Household size > 4	6.1%	3.7%	3.79***	3.1%	3.3%	-0.85
East Germany	24.4%	21.5%	2.61***	19.8%	21.0%	-1.79*
High income	12.2%	5.9%	7.28***	12.8%	11.0%	3.25***

Note: Population data is drawn from Destatis (2008, 2015). This data source asks the main earner to complete the questionnaire, whereas we ask the household member who usually makes the financial decisions for the household. Furthermore, the variable *High income* is top-coded at 4,500 EUR, while in our sample the upper threshold is at 4,700 EUR. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level respectively.

Table A3: First Stage Estimation Results

	Static Models				Dynamic Models			
	Standard 2SLS		Fixed Effects 2SLS		Standard 2SLS		Fixed Effects 2SLS	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
$\ln(z)$	0.244***	(0.020)	0.186***	(0.026)	0.245***	(0.024)	0.228***	(0.048)
$\ln(y_{t-1})$	-	-	-	-	-0.113***	(0.004)	-0.031***	(0.010)
$\ln(\text{Income})$	-0.013***	(0.003)	0.001	(0.007)	-0.003	(0.003)	0.010	(0.010)
Household size = 2	-0.078***	(0.003)	-0.054***	(0.011)	-0.029***	(0.004)	-0.042*	(0.022)
Household size = 3	-0.104***	(0.004)	-0.068***	(0.011)	-0.029***	(0.005)	-0.056**	(0.023)
Household size = 4	-0.121***	(0.004)	-0.074***	(0.013)	-0.028***	(0.006)	-0.033	(0.026)
Household size >4	-0.123***	(0.006)	-0.073***	(0.020)	-0.016**	(0.008)	-0.028	(0.031)
College degree	0.007***	(0.002)	0.006	(0.007)	0.003	(0.003)	0.008	(0.009)
Age	-0.001***	(0.000)	0.000	(0.001)	0.000	(0.000)	0.001	(0.001)
Female	0.005**	(0.002)	0.007	(0.014)	0.004	(0.003)	0.032*	(0.019)
Homeowner	-0.021***	(0.002)	-0.013	(0.013)	-0.003	(0.003)	-0.037**	(0.017)
Constant	2.611***	(0.050)	2.587***	(0.050)	3.529***	(0.076)	2.905***	(0.185)
Year Dummies	Yes		Yes		Yes		Yes	
State Dummies	Yes		Yes		Yes		Yes	
Number of observations	19,026		19,026		8,096		8,096	
F-statistic	237.2		50.2		134.6		25.1	

Note: Standard errors are clustered at the individual level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A4: Random-Effects Estimation Results

	Standard Method		2SLS		Dynamic 2SLS	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
$\ln(p)$	-0.706***	(0.024)	-	-	-	-
$\ln(\widehat{p})$	-	-	-0.209	(0.222)	-0.247*	(0.131)
$\ln(y_{t-1})$	-	-	-	-	0.844***	(0.016)
$\ln(\text{Income})$	0.061***	(0.007)	0.063***	(0.008)	0.003	(0.004)
Household size = 2	0.354***	(0.012)	0.402***	(0.021)	0.070***	(0.007)
Household size = 3	0.530***	(0.013)	0.590***	(0.025)	0.107***	(0.009)
Household size = 4	0.634***	(0.014)	0.696***	(0.029)	0.118***	(0.010)
Household size > 4	0.748***	(0.024)	0.823***	(0.036)	0.144***	(0.011)
College degree	-0.019***	(0.007)	-0.020***	(0.008)	-0.002	(0.004)
Age	0.004***	(0.000)	0.005***	(0.000)	-0.000	(0.000)
Female	-0.013*	(0.006)	-0.013*	(0.007)	-0.002	(0.003)
Homeowner	0.178***	(0.009)	0.186***	(0.011)	0.017***	(0.004)
Constant	9.060***	(0.097)	7.491***	(0.705)	1.924***	(0.567)
Year Dummies	Yes		Yes		Yes	
State Dummies	Yes		Yes		Yes	
Number of observations	21,918		19,026		8,096	
Long-run price elasticity	-	-	-	-	-1.583***	(0.700)

Note: Standard errors are clustered at the individual level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. Standard errors for the long-run elasticities are computed using the delta method.

Table A5: Estimation Results for Dynamic Model (12) based on various Estimation Methods Using Marginal Prices mp .

	2SLS		Fixed Effects 2SLS		Random Effects 2SLS		Blundell-Bond	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
$\widehat{\ln(p)}$	-0.157	(0.186)	0.129	(0.549)	-0.186	(0.182)	-0.562	(0.348)
$\ln(y_{t-1})$	0.887***	(0.008)	0.193***	(0.039)	0.863***	(0.009)	0.412***	(0.106)
$\ln(\text{Income})$	0.001	(0.005)	0.035	(0.030)	0.002	(0.005)	0.034***	(0.013)
Household size = 2	0.070***	(0.008)	0.277***	(0.060)	0.081***	(0.009)	0.283***	(0.050)
Household size = 3	0.100***	(0.010)	0.449***	(0.071)	0.119***	(0.011)	0.437***	(0.077)
Household size = 4	0.108***	(0.011)	0.482***	(0.071)	0.128***	(0.012)	0.481***	(0.085)
Household size >4	0.129***	(0.013)	0.564***	(0.092)	0.155***	(0.014)	0.580***	(0.103)
College degree	-0.002	(0.005)	0.045**	(0.023)	-0.001	(0.005)	-0.018*	(0.010)
Age	-0.000*	(0.000)	0.003	(0.002)	-0.000	(0.000)	0.002***	(0.001)
Female	-0.003	(0.004)	-0.013	(0.029)	-0.003	(0.004)	-0.006	(0.008)
Homeowner	0.013***	(0.004)	0.027	(0.056)	0.015***	(0.005)	0.085***	(0.019)
Constant	1.276**	(0.650)	5.318***	(1.805)	1.531**	(0.639)	5.759***	(1.474)
Year Dummies	Yes		Yes		Yes		Yes	
State Dummies	Yes		Yes		Yes		Yes	
Number of observations	5,485		5,485		5,485		5,485	
Number of instruments	-		-		-		40	
Arellano-Bond test for AR(1)	-		-		-		z=-5.43; p=0.000	
Arellano-Bond test for AR(2)	-		-		-		z=-0.16; p=0.873	
Hansen test of overid. restrictions	-		-		-		$\chi^2(6)=5.76; p=0.450$	
Long-run price elasticity	-1.394	(1.691)	0.160	(0.680)	-1.363	(1.314)	-0.956*	(0.567)

Note: Standard errors are clustered at the individual level. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level respectively. Standard errors for the long-run elasticities are computed using the delta method. The marginal price is calculated by dividing the difference between total expenditures and the fixed fee by the amount of electricity consumed.

Table A6: Robustness Checks for Dynamic Model (12) based on the Blundell-Bond Estimator using Various Ways to Instrument the Lagged Consumption Variable

	First-Differences Instruments Not Collapsed		First-Differences Instruments Collapsed		Orthogonal-Deviations Instruments Not Collapsed	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
$\ln(p)$	-0.461**	(0.187)	-0.508**	(0.240)	-0.511**	(0.204)
$\ln(y_{t-1})$	0.465***	(0.111)	0.384***	(0.102)	0.366***	(0.112)
$\ln(\text{Income})$	0.032***	(0.012)	0.037***	(0.012)	0.038***	(0.012)
Household size = 2	0.229***	(0.048)	0.262***	(0.045)	0.271***	(0.052)
Household size = 3	0.353***	(0.075)	0.406***	(0.068)	0.420***	(0.080)
Household size = 4	0.405***	(0.084)	0.462***	(0.078)	0.476***	(0.090)
Household size > 4	0.488***	(0.106)	0.560***	(0.097)	0.578***	(0.112)
College degree	-0.012	(0.008)	-0.016*	(0.008)	-0.016**	(0.008)
Age	0.002***	(0.001)	0.002***	(0.001)	0.002***	(0.001)
Female	-0.003	(0.007)	-0.003	(0.007)	-0.003	(0.007)
Homeowner	0.072***	(0.019)	0.086***	(0.018)	0.087***	(0.019)
Constant	5.113***	(1.089)	5.805***	(1.190)	6.004***	(1.094)
Year Dummies		Yes		Yes		Yes
State Dummies		Yes		Yes		Yes
Number of observations		8,096		8,096		8,096
Number of instruments		68		41		61
Arellano-Bond test for AR(1)		$z=-4.80; p=0.000$		$z=-5.50; p=0.000$		$z=-4.26; p=0.000$
Arellano-Bond test for AR(2)		$z=1.30; p=0.194$		$z=1.30; p=0.195$		$z=1.13; p=0.258$
Hansen test of overid. restrictions		$\chi^2(34)=26.38; p=0.821$		$\chi^2(7)=2.98; p=0.887$		$\chi^2(27)=24.93; p=0.579$
Long-run price elasticity	-0.862**	(0.337)	-0.825**	(0.366)	-0.8061**	(0.331)

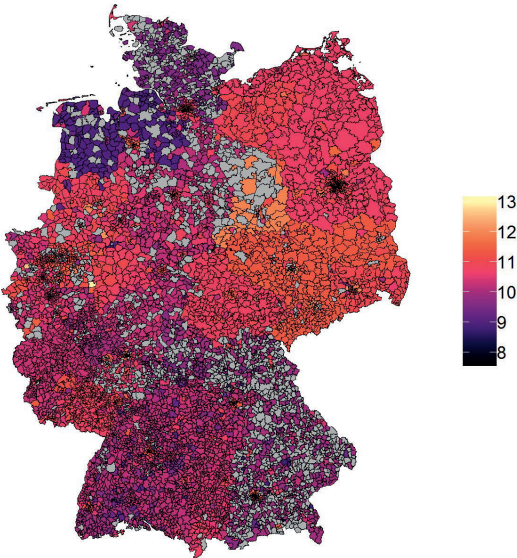
Note: Standard errors are clustered at the individual level. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level respectively. Standard errors for the long-run elasticities are computed using the delta method

Table A7: OLS Estimation Results on the Likelihood of Holding Appliances that are Less Than 5 Years Old

	Refrigerator		Freezer		Dishwasher		Washing Machine		Tumble Dryer	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Middle income	0.020	(0.046)	0.037	(0.060)	0.122**	(0.054)	0.030	(0.046)	0.008	(0.069)
High income	0.011	(0.062)	0.136*	(0.077)	0.116*	(0.069)	0.076	(0.063)	0.001	(0.080)
Homeowner	-0.029	(0.036)	-0.057	(0.046)	-0.009	(0.041)	-0.089**	(0.036)	-0.050	(0.049)
Constant	0.445***	(0.108)	0.166	(0.134)	0.538***	(0.127)	0.571***	(0.112)	0.963***	(0.171)
Further controls		Yes		Yes		Yes		Yes		Yes
Dep. variable means		0.350		0.255		0.363		0.350		0.300
Number of obs.		1,404		920		1,150		1,367		807

Note: The dependent variable is a binary indicator that equals unity if a household holds a respective appliance that is less than five years old and zero otherwise. The high income group comprises household net incomes above €3,500, while the middle income group covers the range between €1,250 and €3,500. Further controls encompass information on age, household size, gender, high school degree, offspring, geography, building type, and employment situation. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1 %, 5 % level, and 10 % level, respectively.

Figure A1: Regional Variation of the Regulated Electricity Price Components (Grid Fees, Levies, and the German Eco-Tax) in Germany in 2006.



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