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The price response of residential electricity demand in Germany: A dynamic approach

Manuel Frondel, Gerhard Kussel, Stephan Sommer

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The Price Response of Residential Electricity Demand in Germany: A Dynamic Approach

Manuel Frondel*, Gerhard Kussel*, Stephan Sommer†

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Abstract. Due to growing concerns about climate change, policy-makers from all around the world establish measures, such as carbon taxes, to lower electricity demand and energy consumption in general. Drawing on household panel data from the German Residential Energy Consumption Survey (GRECS) that span over nine years (2006-2014) and employing the sum of regulated price components as an instrument for the likely endogenous electricity price, 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 the 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.

Keywords: Dynamic panel methods, Instrumental variable approach.

JEL codes: C23, C26, D12, Q41.

Correspondence: Manuel Frondel, RWI – Leibniz Institute for Economic Research, Hohenzollernstr. 1-3, D-45128 Essen. Email: frondel@rwi-essen.de.

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*RWI Leibniz Institute for Economic Research and Ruhr University Bochum
†RWI Leibniz Institute for Economic Research

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. By 2030, the European Union (EU), for instance, 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 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).

Drawing on household panel data from the German Residential Energy Consumption Survey (GRECS) that span over nine years, from 2006 to 2014, and using the sum of the regulated price components as an instrument to cope with the likely endogeneity of electricity prices, this paper estimates the response of household electricity demand to price changes on the basis of the dynamic system estimator developed by

Blundell and Bond (1998). By comparing these estimates with those resulting from both OLS and standard panel methods, we demonstrate that price elasticity estimates may be biased if the methodological challenges due to 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: Using 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, based on a single survey wave of the GRECS comprising the years 2011 and 2012, Frondel and Kussel (2018) obtain a short-run price elasticity estimate of -0.52. Yet, exploiting information on households' knowledge about electricity price levels, these authors find that only those households that are informed about prices are sensitive to price changes, whereas uninformed households are entirely price-inelastic.

Our results indicate that, at least to some extent and particularly in the log 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). Furthermore, exploiting the abundance of our data set by estimating dynamic models for specific groups of households individually, a distinguishing feature of our study is the finding that price responses are heterogeneous across household groups: Wealthy households, for instance, exhibit a particularly strong demand reaction, while we do not find any price response for some other groups, such as low-income households. These results suggest that increasing electricity prices, for instance via introducing or raising a carbon tax, may not be a universally effective means. Therefore, to reduce energy 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 subsidies for the purchase of energy-efficient appliances, and focus on low-income households.

Given its ambitious climate policy goals, prominently reflected by the aim to increase the share of renewable-based electricity in gross consumption to 35% by 2020, Germany suggests itself as an interesting case study for the analysis of demand reactions to power price increases. As a consequence of Germany's cost-intensive climate policy (Frondel et al., 2015), with about 30 cents per kilowatt-hour (kWh), German households face the highest electricity prices in the EU in terms of purchasing power standards (Andor et al., 2017). 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 (BMWi, 2018), the levy for the support of renewable technologies rose substantially, from 0.30 to 6.79 cents per kWh in 2018, now contributing to household electricity prices by more than a fifth (BDEW, 2017).

The subsequent section describes the database underlying our research, while Section 3 explains the empirical methodology employed. Section 4 presents the estimation results. The last section summarizes and concludes.

2 Data

This 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' most recent electricity bills, covering the years prior to each survey year. In the best case, a household head reported electricity information for up to $T = 9$ years. Yet, this was the case for only 3 households, but 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 and household net income, age and education of the household head, 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 (RWI and forsa, 2018). *forsa*'s survey tool allows respondents to interrupt and continue the survey at any time and to complete the questionnaire either online or, if internet access is not available, using a television.

The billing information include 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 calender 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 the fact that we generously have sacrificed 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]

While 31% of the respondents have a college degree (Table 1), about one third of them are female and, thus, women are considerably less frequent in the sample than men. This circumstance 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. The high share of respondents with a college degree in our sample indicates that it 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.

Table 1: Descriptive Statistics

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 A3 in

[1]Households 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.

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 do afflict both average and marginal prices, as nowadays consumers are free to choose from a broad range of electricity tariffs: since the liberalization 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): while, on the one hand, consumption levels tend to be affected by prices, on the other hand, households' tariff selection may depend on consumption levels. In short, as household electricity consumption levels and electricity prices are jointly determined, one must recognize that both marginal and averages prices are likely to be endogenous.

Figure 1 provides a first notion on the relationship between average household prices and their annual electricity consumption as resulting from our sample in the survey period 2006-2014. Mean annual electricity consumption decreased from 3,807 kWh in 2006 to 3,111 kWh in 2014, whereas the average electricity price 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 4 can be obtained by dividing the relative consumption decrease by the percentage price increase. This crude back-of-the-envelope calculation yields an estimate of the long-run price elasticity of -0.489 for the period 2006 to 2014.

The average prices resulting from the sample closely match the mean prices that are reported by the German Association of Energy and Water Industries (BDEW, 2017) 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 and rose 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

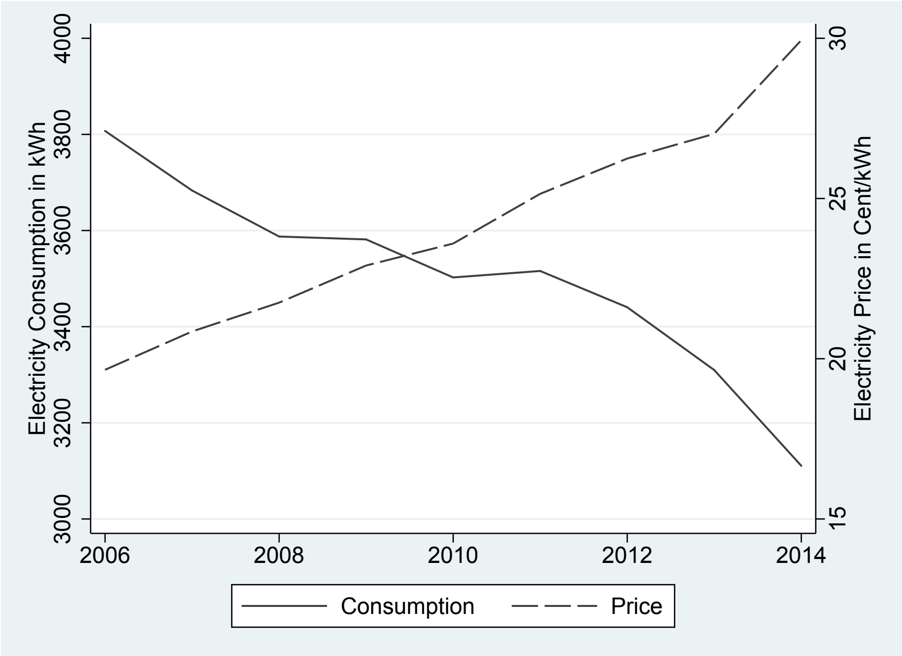

Figure 1: Mean Household Electricity Consumption per Year and Average Household Electricity Prices in Cents per Kilowatt-hour Resulting from the German Residential Energy Consumption Survey (GRECS).

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).

Another substantial electricity price component are grid fees, which have moderately increased over time, but vary substantially across regions. Grid fees are raised to cover maintenance costs, as well as the costs that grid operators arise 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, we employ the sum of regulated price components, consisting of grid and concession fees, levies, and the German eco-tax, a tax on electricity use of 2.05 cents per kWh. Hence, except for

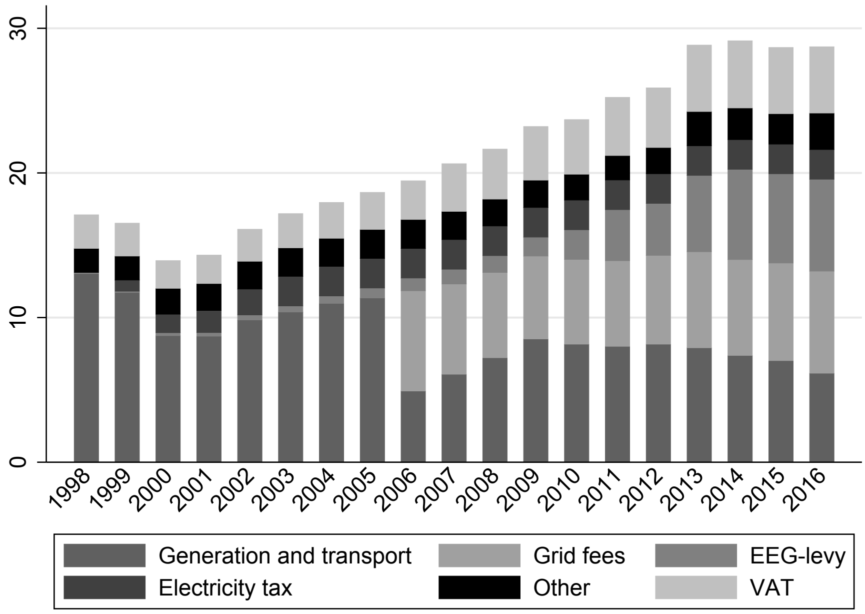

Figure 2: Composition of Household Electricity Prices for a Household Consumption of 3,500 kWh per Year (Source: BDEW, 2017).

generation and transport cost, as well as the VAT, instrumental variable z comprises all other elements illustrated by Figure 2. 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, mainly caused by a strong deployment of renewable energy installations that resulted in both a higher EEG levy and higher costs for connecting new installations (Andor et al., 2017).

Figure 3 illustrates that the regulated price components as captured by instrument z exhibits strong regional variation, both across, but also within federal states, and varied 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.

With a correlation coefficient of $\rho = 0.68$ that reflects the expected positive correlation between the average price p and our 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

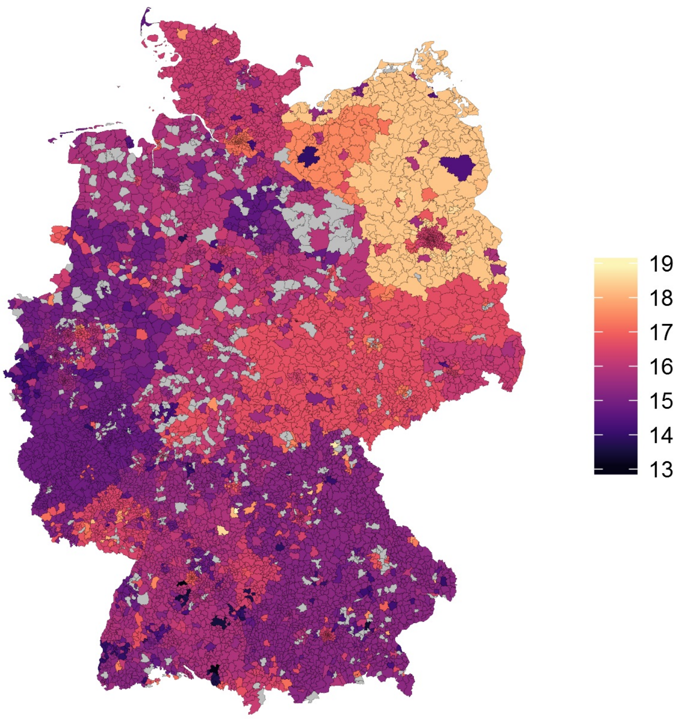

Figure 3: Regional Variation of the Regulated Electricity Price Components (Grid Fees, Levies, and the German Eco-Tax) in Germany in 2014.

all households, the sum of these price components is the same for all households of a 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 any regression equation.

3 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:

$$\ln y_{it} = \beta + \beta_p \ln p_{it} + \boldsymbol{\beta}_{\mathbf{x}}^T \mathbf{x}_{it} + \tau_t + \mu_i + \nu_{it}, \tag{1}$$

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 $\boldsymbol{\beta}_{\mathbf{x}}$ 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 ν_{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 in such a setting, the natural set of instruments are components of the price schedule itself. 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 $\mathbf{x}$:

$$\ln p_{it} = \gamma + \gamma_z \ln z_{it} + \boldsymbol{\gamma}_{\mathbf{x}}^T \mathbf{x}_{it} + \tau_t + \mu_i + u_{it}. \tag{2}$$

In the second stage, the price prediction $\widehat{p}$ obtained from Equation (2), rather than the actual price p, is employed to estimate Equation (1).

The static model given by Equation (1) 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, however, 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:

$$\ln y_{it} = \beta + \beta_y \ln y_{i,t-1} + \beta_p \ln p_{it} + \boldsymbol{\beta}_{\mathbf{x}}^T \mathbf{x}_{it} + \tau_t + \mu_i + \nu_{it}, \tag{3}$$

with ν_{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 (3) 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 $\mu_i + \nu_{it}$. For the same reason, estimating Equation (3) using random-effects estimation methods yields inconsistent estimates as well. In what follows, for comparison purposes, we nonetheless report random-effects estimates, in addition to the results based on the dynamic Blundell-Bond estimator that is employed to account for potential simultaneity and endogeneity problems.

Moreover, when Equation (3) 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 ν_{it} were to be independent and identically distributed.

One alternative to consistently estimate Equation (3) involves taking first differences of the original Model (1) to eliminate the problems arising from the individual effects μ_i:

$$\Delta \ln y_{it} = \beta_y \Delta \ln y_{i,t-1} + \beta_p \Delta \ln p_{it} + \boldsymbol{\beta}_{\mathbf{x}}^T \Delta \mathbf{x}_{it} + \Delta \tau_t + \Delta \epsilon_{it}, \tag{4}$$

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 $\Delta \nu_{it} := \nu_{it} - \nu_{i,t-1}$ as long as the error terms ν_{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, these authors 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 ν_{it} (Blundell and Bond, 1998, p.118): $E(y_{i,t-s}\Delta\nu_{it}) = 0$ for $t = 3, \ldots, T$ 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 $(\nu_{i3} - \nu_{i2})$ 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 $y_{i1}, y_{i2}, \ldots, y_{i,T-2}$ 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, ... 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.

4 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.

4.1 Results from the Static Model

Using the results originating from static Model (1) as a reference case for the outcomes obtained from dynamic Model (3), 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 unity, a magnitude that is well-know 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.

Table 2: Estimation Results for Static Model (1) on Electricity Demand based on various Estimation Methods.

	OLS		2SLS		Random Effects		Random Effects 2SLS	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
$\ln(p)$	-1.403***	(0.024)	–	–	-0.706***	(0.024)	–	–
$\widehat{\ln(p)}$	–	–	-0.639***	(0.203)	–	–	-0.209	(0.222)
ln (Income)	0.064***	(0.005)	0.076***	(0.006)	0.061***	(0.007)	0.063***	(0.008)
Household size = 2	0.355***	(0.007)	0.414***	(0.017)	0.354***	(0.012)	0.402***	(0.021)
Household size = 3	0.571***	(0.008)	0.652***	(0.023)	0.530***	(0.013)	0.590***	(0.025)
Household size = 4	0.661***	(0.009)	0.752***	(0.027)	0.634***	(0.014)	0.696***	(0.029)
Household size > 4	0.833***	(0.013)	0.922***	(0.029)	0.748***	(0.024)	0.823***	(0.036)
College degree	-0.028***	(0.005)	-0.032***	(0.006)	-0.019***	(0.007)	-0.020***	(0.008)
Age	0.004***	(0.000)	0.005***	(0.000)	0.004***	(0.000)	0.005***	(0.000)
Female	-0.001	(0.005)	-0.006	(0.005)	-0.013*	(0.006)	-0.013*	(0.007)
Homeowner	0.137***	(0.005)	0.152***	(0.007)	0.178***	(0.009)	0.186***	(0.011)
Constant	11.091***	(0.089)	8.642***	(0.648)	9.060***	(0.097)	7.491***	(0.705)
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.

When exploiting the panel structure of our data, we prefer reporting random-effects, rather than fixed-effects estimation results, even though the null hypothesis of equal sets of coefficient estimates of the Hausman (1978) specification test is rejected. While the short-run price elasticity estimate obtained from the random-effects estimator amounts to about -0.71 (Table 2), we argue that applying fixed-effects estimation methods is not appropriate for our IV approach, because our instrumental variable consists of uniform price components, such as the EEG levy, that only vary inter-temporally, as well as regional-specific fees that mainly exhibit spatial variation, but are rather constant over time. Hence, accounting for both time- and individual effects would eliminate much of the variation in our instrument. As a consequence, the fixed-effects estimation results reported in Table A4 in the Appendix are considerably lower than those obtained by using random-effects methods, with the price elasticity estimates resulting from both the static and dynamic 2SLS fixed-effects estimations being statistically insignificant.

By additionally instrumenting our price variable to address simultaneity issues, the resulting 2SLS random-effects estimate of the short-run price elasticity is as low as -0.21 and, given the standard error of 0.22, not significantly different from zero in statistical terms. For the remaining covariates, coefficient estimates do not vary much across estimation methods. In addition to prices, to a large extent, electricity consumption is driven by a couple of major factors, such as household size and income. For instance, based on the random-effects 2SLS estimates, the average electricity consumption of a household with two members is about $100[exp(0.402)-1]$ =49% higher than that of a single-person household. Likewise, homeowners and households with elder individuals tend to have a higher consumption than other households. Furthermore, a 10% increase in income leads to a 0.63% increase in electricity demand. While at first glance this income elasticity estimate appears particularly low, it may be the result of two opposing effects: as is characteristic for normal goods, the demand for electric services increases with income. However, a higher income allows to invest in new and more efficient appliances, thereby dampening electricity demand (Spees and

Lave, 2007).

4.2 Results from the Dynamic Model

As static models fail to account for sluggish adjustments of the appliance stock, we continue reporting the estimates from dynamic Model (3), in which lagged electricity consumption is included as an additional variable to control for adjustments in the appliance stock. 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 (3), 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 random-effects estimation methods yields estimation results that are close to those obtained by 2SLS.

Given that in a dynamic setting fixed-effects estimation methods suffer from the Nickell bias, we present the results originating from the Blundell-Bond GMM system estimator.[2] Both the coefficient estimates on the price 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 data, Nikodinoska and Schröder (2016) as well as Schulte and Heindl (2017) find long-run elasticities of -0.81 and -0.43, respectively.

[2]To this end, the Stata command xtabond2 written by Roodman (2009a) has been employed. Table A5 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.

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

	2SLS		Random Effects 2SLS		Blundell-Bond	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
$\widehat{\ln(p)}$	-0.229*	(0.137)	-0.247*	(0.131)	-0.444*	(0.236)
$\ln(y_{t-1})$	0.864***	(0.016)	0.844***	(0.016)	0.330***	(0.104)
ln (Income)	0.002	(0.004)	0.003	(0.004)	0.042***	(0.011)
Household size = 2	0.063***	(0.007)	0.070***	(0.007)	0.292***	(0.047)
Household size = 3	0.094***	(0.009)	0.107***	(0.009)	0.455***	(0.072)
Household size = 4	0.103***	(0.009)	0.118***	(0.010)	0.514***	(0.082)
Household size > 4	0.126***	(0.010)	0.144***	(0.011)	0.624***	(0.101)
College degree	-0.002	(0.004)	-0.002	(0.004)	-0.018**	(0.008)
Age	-0.000	(0.000)	-0.000	(0.000)	0.003***	(0.001)
Female	-0.002	(0.003)	-0.002	(0.003)	-0.003	(0.007)
Homeowner	0.015***	(0.004)	0.017***	(0.004)	0.095***	(0.018)
Constant	1.728***	(0.590)	1.924***	(0.567)	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)	-1.583**	(0.700)	-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.

Statistical tests indicate the validity of the Blundell-Bond estimates, with the results benefitting from the large number of $N = 8,096$ 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 (4). (This test is important because the consistency of the GMM estimator relies upon the fact that $E[\Delta\nu_{it}\Delta\nu_{i,t-2}] = 0$.) The p-value of $p = 0.249$ 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 (3). 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 (3). Finally, the Hansen test of overidentifying restrictions indicates that the null hypothesis of the joint validity of the instruments cannot be rejected. This test does not only show that our set of instruments is valid, but also that the model is correctly specified (Roodman, 2009b).

4.3 Heterogeneous Effects

Building upon our preferred estimation method, the Blundell-Bond estimator, and exploiting the abundance of our data set with respect to socioeconomic characteristics by estimating dynamic Model (3) for specific groups of households individually, we find a large heterogeneity in price responses across household groups (Table 4). Focusing first on the group of high-income households, defined here by a monthly household net income above €3,500, the results reported in Table 4 suggest that their price responsiveness is substantially higher than that of other households, with short- and long-run price elasticity estimates amounting to -0.86 and -1.29, respectively, for such high-income households. Being in line with Schulte and Heindl (2017) and Nikodinoska and Schröder (2016), the finding that high-income households are highly responsive to price changes reflects the fact that, in contrast to other household groups, they can more easily react to price increases by adjusting their appliance stock towards less electricity-intensive equipment.

A similar argument can be made for homeowners, as opposed to tenants, when assuming that homeowners tend to have a higher rent-corrected income than tenants. And, in fact, we find strong and statistically significant price responses for homeowners, yet not for tenant households. This effect can also be caused by the so-called landlord-tenant problem (Allcott and Greenstone, 2012): If landlords bear the tenants' marginal cost of electricity consumption, tenants have little incentive to use electricity efficiently (Levinson and Niemann, 2004). Conversely, if tenants themselves face electricity costs, landlords can choose to equip the rental apartments with energy-inefficient appliances. Both ideas provide an explanation for Davis' (2011) finding that tenants are less likely to have energy-efficient appliances.

In addition, there is evidence that households whose head has a college degree strongly react to prices, but there is no price responsiveness among household heads

Table 4: Heterogeneous Electricity Demand Responses to Price Changes across various Household Groups

	$\ln(y_{t-1})$		$\widehat{\ln(p)}$		Long-run Price Elasticity		No. of
	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	observations
Low-income household	0.251	(0.413)	-0.424	(0.628)	-0.57	(0.887)	1,232
High-income household	0.336*	(0.155)	-0.855**	(0.352)	-1.29***	(0.477)	2,215
Tenant	0.311	(0.259)	-0.281	(0.418)	-0.41	(0.593)	2,899
Homeowner	0.337***	(0.103)	-0.715***	(0.210)	-1.08***	(0.278)	5,197
No college degree	0.210	(0.133)	-0.334	(0.296)	-0.42	(0.367)	5,552
College degree	0.499**	(0.130)	-0.645**	(0.279)	-1.29**	(0.508)	2,554

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. All models include socioeconomic characteristics as well as year and state dummies.

without a college degree (Table 4). Assuming that individuals with a college degree are better informed about electricity prices than others, these results confirm those of Jessoe and Rapson (2014) and Frondel and Kussel (2018), who find that the electricity demand of uninformed households is entirely price-inelastic.

5 Summary and Conclusions

The residential sector accounts for a substantial share of electricity demand in industrialized countries, for example being responsible for about a quarter of Germany's total electricity consumption (AGEB, 2016). Establishing 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 prices may have substantially adverse regressive effects for low-income households (Frondel et al., 2015; Heindl and Schüssler, 2015; Neuhoff et al., 2013). 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. Moreover, the effectiveness of such price measures critically hinges on the magnitude of the price elasticity of household demand.

Drawing on household panel data from the German Residential Energy Consumption Survey (GRECS) that span over nine years (2006-2014), in this paper, we have 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. 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 the estimates of price elasticity may be biased if the resulting 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 to some extent and 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. Furthermore, our long-run price elasticity estimate of -0.66 implies that, to reach Germany's aim to lower electricity consumption by 10% relative to 2008 by 2020, the average electricity price needs to be 15.2% higher in 2020 than in 2008.

This requirement is most likely to be more than fulfilled by 2020 for our sample households, as the average electricity price in the sample increased from 21.8 cents per kWh in 2008 to 29.9 cents in 2014, that is, by almost 40%, not least due to Germany's strong promotion of renewable energy technologies. In the same period, the mean annual consumption of our sample households fell by around 13%, from 3,586 to 3,111 kWh, while based on our long-run elasticity estimate of -0.66, we would expect the residential consumption to have shrank by about 26%. This discrepancy between the actual and inferred percentage reductions is likely the result of several secular trends that *ceteris paribus* increase the electricity consumption of the residential sector, such as the increase in households' appliance stock and, most notably, the ever-growing number of single- and two-person households, whose per-capita consumption is higher than for households with more members.

Moreover, exploiting the abundance of our data set by estimating dynamic models for specific groups 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 and highly educated households, in particular, low-income households 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, calling for additional non-pricing measures to reduce the greenhouse gas emissions originating from fossil-based electricity consumption.

Yet, the absence of any price responses among certain household groups has important implications for energy conservation programs that include non-pricing measures, such as energy audits and subsidies for the purchase of energy efficient appliances (Allcott et al., 2015; Fowlie et al., 2015): These programs may target at household groups that do not seem to respond to price increases, such as low-income households. Targeted programs that focus on these groups may ensure a more effective usage of resources than unspecific programs.

Appendix

Table A1: Frequency in the Response of Households and Number of Observations

Number of Responses	Frequency	Share	Cumulated	Number of Observations
1	4,421	40.50	40.50	4,421
2	3,100	28.40	68.91	6,200
3	1,682	15.41	84.32	5,046
4	727	6.66	90.98	2,908
5	486	4.45	95.43	2,403
6	235	2.15	97.58	1,410
7	194	1.78	99.36	1,358
8	67	0.61	99.97	536
9	3	0.03	100.00	27
Total	10,915	100.00		24,336

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

	2006		2014	
Variable	Sample	Population	Sample	Population
Age under 25 years	3.3%	5.0%	0.4%	4.7%
Age 25 – 64 years	83.6%	67.7%	67.3%	67.0%
Age 65 years and more	13.1%	27.2%	32.3%	28.1%
College degree	33.7%	15.7%	35.7%	19.0%
Female	32.3%	34.1%	31.0%	35.4%
Household size = 1	19.4%	38.8%	22.7%	40.8%
Household size = 2	38.6%	33.6%	53.0%	34.4%
Household size = 3	19.0%	13.5%	12.2%	12.4%
Household size = 4	16.7%	10.3%	9.0%	9.1%
Household size > 4	6.3%	3.7%	3.1%	3.3%
East Germany	21.7%	21.5%	19.3%	21.0%
High income	12.0%	5.9%	12.7%	11.0%

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.

Table A3: Estimation Results for Dynamic Model (3) based on various Estimation Methods Using Marginal Prices mp.

	2SLS		Random Effects 2SLS		Blundell-Bond	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
$\widehat{\ln(mp)}$	-0.157	(0.186)	-0.186	(0.182)	-0.562	(0.348)
$\ln(y_{t-1})$	0.887***	(0.008)	0.863***	(0.009)	0.412***	(0.106)
ln (Income)	0.001	(0.005)	0.002	(0.005)	0.034***	(0.013)
Household size = 2	0.070***	(0.008)	0.081***	(0.009)	0.283***	(0.050)
Household size = 3	0.100***	(0.010)	0.119***	(0.011)	0.437***	(0.077)
Household size = 4	0.108***	(0.011)	0.128***	(0.012)	0.481***	(0.085)
Household size > 4	0.129***	(0.013)	0.155***	(0.014)	0.580***	(0.103)
College degree	-0.002	(0.005)	-0.001	(0.005)	-0.018*	(0.010)
Age	-0.000*	(0.000)	-0.000	(0.000)	0.002***	(0.001)
Female	-0.003	(0.004)	-0.003	(0.004)	-0.006	(0.008)
Homeowner	0.013***	(0.004)	0.015***	(0.005)	0.085***	(0.019)
Constant	1.276**	(0.650)	1.531**	(0.639)	5.759***	(1.474)
Year Dummies	Yes		Yes		Yes	
State Dummies	Yes		Yes		Yes	
Number of observations	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	-1.389	(1.691)	-1.358	(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 conmputed by dividing the difference between total expenditures and the fixed fee by the amount of electricity consumed.

Table A4: Fixed-Effects Estimation Results

	Fixed Effects		Fixed Effects 2SLS		Fixed Effects 2SLS (dynamic)	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
$\ln(p)$	-0.486***	(0.026)	–	–	–	–
$\widehat{\ln(p)}$	–	–	0.076	(0.288)	-0.093	(0.325)
$\ln(y_{t-1})$	–	–	–	–	0.188***	(0.039)
ln (Income)	0.000	(0.012)	-0.006	(0.013)	0.003	(0.017)
Household size = 2	0.225***	(0.023)	0.261***	(0.033)	0.251***	(0.049)
Household size = 3	0.347***	(0.025)	0.390***	(0.037)	0.392***	(0.056)
Household size = 4	0.414***	(0.027)	0.449***	(0.040)	0.431***	(0.056)
Household size > 4	0.437***	(0.043)	0.486***	(0.054)	0.407***	(0.074)
College degree	0.009	(0.015)	0.006	(0.016)	0.008	(0.019)
Age	0.002	(0.002)	0.002	(0.002)	0.003	(0.002)
Female	-0.004	(0.019)	0.003	(0.018)	0.017	(0.022)
Homeowner	0.128***	(0.031)	0.144***	(0.036)	0.041	(0.036)
Constant	9.107***	(0.165)	7.424***	(0.886)	6.328***	(1.233)
Year Dummies	Yes		Yes		Yes	
State Dummies	Yes		Yes		Yes	
Number of observations	21,918		19,026		9,391	
Long-run price elasticity	–	–	–	–	-0.115	(0.398)

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 Robustness Checks for Dynamic Model (3) based on the Blundell-Bond Estimator using Various Ways to Instrument the 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 (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

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