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Sensitivity of price elasticity of demand to aggregation, unobserved heterogeneity, price trends, and price endogeneity: Evidence from U.S. Data

By

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Abstract

Price elasticity estimates of residential electricity demand vary widely across the economic literature. In this paper, we seek to explain these findings using three nationwide datasets – the American Housing Survey, Forms EIA-861, and the Residential Energy Consumption Survey – from the U.S. We examine the role of the sample period, level of aggregation, use of panel data, use of instrumental variables, and inclusion of housing characteristics and capital stock. Our findings suggest that price elasticities have remained relatively constant over time. Upon splitting our panel datasets into annual cross sections, we do observe a negative relationship between price elasticities and the price variance. Whether prices are rising or falling appears to have little effect on our estimates. We also find that aggregating our data generally produces lower price elasticity estimates, as does controlling for unit level fixed effects when using panel data. Addressing the endogeneity of price and/or measurement error in price with instrumental variables has a small but noticeable effect on the price elasticities. Finally, controlling for housing characteristics and capital stock produces a lower price elasticity.

Keywords: residential electricity demand; price elasticity of demand; household-level data; rebound effect; energy demand forecast.

JEL Classification: Q41, D12.

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1. Introduction

Price elasticity estimates for residential electricity demand vary widely across the economic literature. Alberini et al. (2011) review a number of studies, and suggest that differences might be due to the sample period, the nature of the data—such as panels (Maddala et al., 1997; Metcalf and Hasset, 1999; Garcia-Cerrutti, 2000; Bernstein and Griffin, 2005; Alberini et al., 2011) v. pseudo-panels (Bernard et al., 2011), cross-sections (Nesbakken, 1999; Krishnamurthy and Kriström, 2013; Quigley and Rubinfeld, 1989; Boogen et al., 2014; Reiss and White, 2005; Gans et al., 2013), or time series (Kamerschen and Porter, 2004, or Dergiades and Tsoulfidis, 2008)—geography, and level of aggregation of the data. In more recent studies, the price elasticity of electricity consumption ranges from as low as -0.06 (Blazquez et al., 2013) to as high as -1.25 (Krishnamurthy and Kriström, 2013). In general, it is assumed that the price elasticity of demand for electricity is low; a meta-analysis by Espey and Espey (2004), for example, reports that the median short run elasticity for 36 studies is -0.28.

The purpose of this paper is to systematically investigate the possible causes of such large variation. This is not mere intellectual curiosity, given the importance of the price elasticity of demand in utilities infrastructure planning, and energy and environmental policy analysis. For example, the Energy Information Agency uses short-run elasticities of -0.12 to -0.21 and a long-run elasticity of -0.40 when projecting residential energy demand over 25 years under different electricity and natural gas price scenarios (EIA, 2014). These low elasticities imply limited fuel switching and result in relatively small changes in the numbers of electric furnaces, air-source heat pumps, and gas heating equipment.

Given much recent interest and policy focus on improving residential energy efficiency, some observers have voiced concern over the rebound effect, namely the increase in energy use due to the fact that improved energy efficiency lowers the price per unit of energy services. The rebound effect erodes the efficiency gains and, if sufficiently pronounced, may even offset them completely. The key parameter for predicting the end outcome of improvements in energy efficiency is the elasticity of energy demand with respect to efficiency, and this in turn can be shown to be equal to the negative of the price elasticity of demand, minus one (Sorrell and Dimitropoulos, 2008; Sorrell, 2007). Based on this identity and available estimates of the price elasticity on demand, Sorrell and Dimitroupolos conclude that the rebound effect in residential energy use is relatively small.[2, 3] The price elasticity of demand is also a key determinant of the burdens falling on the shoulders of generators and consumers in the presence of a carbon tax, the remedy that has been put in place in some countries (e.g. Australia, Great Britain, and Sweden[4]) to encourage a shift away from fossil fuel usage and the associated CO2 emissions.

We examine seven possible factors that may explain why there is so much variation in the estimate of the price elasticity of electricity demand. The first possible reason is the period over which the elasticity was estimated, which in earlier research has spanned from one year (Krishnamurthy and Kriström, 2013) to over 40 years (Dergiades and Tsoulfidis, 2008). Another is whether over that period the price of electricity was rising or falling. Previous studies have examined this hypothesis, although they are limited to macro data (Gately and Huntington, 2002; Ryan et al, 1996). A third issue concerns the level of data aggregation, a recurring subject of concern as a source of bias (Bohi, 1981; Blundell et al, 1993; Blundell and Stoker, 2005). Aggregation reduces the variation in price, a key factor in identifying its elasticity of demand, and conceals the heterogeneity across more disaggregated units.

[2] By contrast, Davis (2008) uses actual energy use measurements in a randomized controlled trial featuring high-efficiency clothes washer to show that the rebound effect is negligible.
[3] Gillingham et al. (2013) deploy a similar approach and arrive at similar conclusions with cars and driving.
[4] For full list of countries, see http://www.carbontax.org/ (last accessed 31 August 2015).

When the data used for estimating residential energy demand are a panel, another important issue is the degree to which unobserved heterogeneity is accounted for, along with the associated matter of variation in price. Does most of the variation in price come from within units over time, or is it primarily occurring between the units? We expect the "within" estimator typically used with fixed-effects models to perform poorly in the presence of low variation within units over time.

Comparing estimates between studies is further complicated by how prices are measured. Studies in this field are typically subject to endogeneity of price and/or measurement error. First, prices are not always available at the individual household level (Alberini et al., 2011). Second, many studies are forced to rely on average price paid per kilowatt-hour (kWh) even though the original pricing structure faced by the household is a two-part tariff or block pricing. This makes price endogenous with consumption.[5] Endogeneity and/or measurement error can be addressed using instrumental variable (IV) estimation, and the success of this procedure depends crucially on the availability and quality of the instruments.

Finally, we consider the detail of the information available about the household or the dwelling. In recent years, several papers (Auffhammer et al. 2014; Ito, 2014; Allcott, 2011; and Allcott and Rogers, 2014) have deployed panel datasets provided by utilities, with electricity usage readings at a high level of granularity, but virtually no information about the household or the home, despite the importance of behavioral aspects and of the structural characteristics of the dwelling in influencing consumption patterns.[6]

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[5] The matter is even more complicated in the presence of different pricing schemes for each household, as is the case when special offers, discounts etc. are introduced. Langer and Miller (2013) discuss the importance of manufacturing pricing and discounts in the case of car sales, showing that model estimation results and the coefficient(s) on price change dramatically when such discounts and special offers are controlled for.

[6] Alberini and Towe (2015) show that the effects of replacing certain types of electricity-using equipment are captured more sharply when one conditions on past usage *and* home characteristics.

To help reconcile the differences in price elasticity estimates that pervade this literature, we examine if, and how, each of these seven issues may be playing a role. We use three public, nationwide datasets from the U.S. – the American Housing Survey (AHS), the Residential Energy Consumption Survey (RECS), and the Energy Information Agency's (EIA) Forms EIA-861. The former two provide information about electricity consumption at the household level, and the latter at the utility level.

To see how sensitive price elasticities are to the sample period, we exploit the panel nature of the AHS and EIA datasets, create cross sections for each wave, and run regressions for each year. We also construct a fixed effects model for the full panel dataset, and include in our regressions the price interacted with a dummy denoting whether the price has been rising or otherwise relative to the previous year. The price elasticities from these regressions are shown to be relatively stable over time, although in the case of the Forms EIA-861 the estimates also appear to be estimated rather imprecisely. Our results also suggest that whether the prices are increasing or otherwise makes little difference on the estimates of the price elasticities.

Next, we explore the issue of aggregation bias by first estimating models using the micro data, and then by aggregating electricity usage, prices, etc. to the metropolitan area or state level for the AHS, and state level for Forms EIA-861. The evidence from our experiment is mixed. With the AHS, more aggregation results in a more inelastic demand, whether or not we include fixed effects for the cross-sectional unit being considered in that run. With the Forms EIA-861 data, more aggregation sometimes implies a more elastic demand, depending on the model specification, although this effect is smaller when our models include cross-sectional-unit fixed effects. These results are broadly consistent with Halvorsen and Larsen (2013), who show that the effect of aggregation depends crucially on the distribution of price and household income in the sample.

We also examine how the price elasticities change when we control for unobserved heterogeneity. With both the AHS and Forms EIA-861 datasets, including cross-sectional-unit fixed effects always produces a more inelastic demand function. One reason for this result might be the limited "within" variation, as we observe that the "between" variation in price across our units always trumps the "within unit" variation.[7] Another reason might be that omitting the fixed effects biases the price elasticities.

To examine the effect of instrumental variables we work with the micro level data for both the AHS and Forms EIA-861 datasets, and our instrument is the state-level price of electricity. However, the price elasticities from Two Stage Least Squares (2SLS) are quite similar to their Ordinary Least Squares (OLS) counterparts. Should this be caused by instruments of poor quality, we turn to the 2009 RECS, where we experiment with two alternate instruments. The first is the average state-level price, and the second is a cross-validation (CV) instrument, where the instrument for each household's price is the average of the price faced by all other households in the same state. The results are similar across instruments, and indicate a reasonably large change when going from OLS to 2SLS.

Finally, from the 2009 RECS, we find that controlling for housing characteristics and capital stock produces lower price elasticity estimates. This is consistent with what we would expect, since controlling for capital stock produces short run price elasticities. Controlling for capital stock also tends to reduce the income elasticity of demand (capital stock and income tend to be highly correlated).

[7] This is typical with data from the US, where the presence of different jurisdictions (states and counties) almost always ensures greater variation across jurisdictions than over time within a jurisdiction. Datasets from other countries may exhibit the opposite features.

The remainder of this paper is organized as follows. Section 2 reviews the literature. Section 3 discusses our empirical methodology, and Section 4 describes our datasets in more detail. We present our results in Section 5. Section 6 concludes.

2. Previous literature

Alberini et al. (2011) summarize estimates of the price elasticity of demand from earlier studies. We provide an updated assessment of select studies in Table 1. Clearly, the variation in the price elasticity is substantial. The absolute value of estimates range from near zero to over one; a majority fall below 0.5. Possible reasons for such variation may include each study's geography, study period, and hence variation in prices.

To illustrate, some studies are more limited in terms of geography, such as Garcia-Cerutti (2000), which considers county-level data only for the state of California. Others are limited in the number of time periods. Reiss and White (2005), for example, use household level, cross-section data for California for 1993 and 1997, and Boogen et al. (2014) use Swiss household level, cross sectional data for 2005 and 2011. Price variation may also be influenced by the type of data that is used. Most studies in Table 1 use panel data to exploit the variation in price within units over time. However, several remain confined to cross sections or time series (Kamerschen and Porter, 2004; Dergiades and Tsoulfides, 2008).

Based on Table 1, it would seem that in recent years sample sizes have grown as a result of longer time series and wider cross sections, and data have been more available at more disaggregated levels such as the state (Paul et al., 2009; Alberini and Filippini, 2010), census block group (Borenstein, 2009), or household (Boogen et al., 2014; Fell et al., 2014; Alberini et al., 2011). In the absence of true panels, Bernard et al. (2011) construct a pseudo-panel using four waves of survey data from Quebec that results in only 108 observations.

The question of the importance of rising or falling prices during the study period has received some attention in the literature. Haas and Schipper (1998), Gately and Huntington, (2002), and Ryan et al. (1996) examine this issue at the national level with time series data, and support the notion that investments in energy efficiency during periods of higher prices may result in little sensitivity to price changes when prices decline.

The issue of aggregation and aggregation bias is well studied in the econometrics literature (Blundell et al, 1993; Blundell and Stoker, 2005; and Stoker, 1993). From Table 1, we note that with a few exceptions (e.g. Kamerschen and Porter, 2004), studies with highly aggregated data appear to produce lower price elasticity estimates than their disaggregated counterparts. However, the effect of aggregating is not necessarily monotonic. Bohi (1993), in his review of the energy demand literature, explains that theory predicts that bias is likely to occur with aggregation; however, it cannot directly inform us on the magnitude and direction of such bias, making it an empirical question.[8] In the context of electricity, aggregation has been most directly examined by Halvorsen and Larsen (2013), who find that price elasticities estimated from aggregated micro-data and macro-data are lower than those estimated directly from micro data, and in some cases even positive. Using the framework of a quasi Almost Ideal Demand System model ("quasi" because consumption, rather than budget share, is used as the outcome variable), they demonstrate that the differences between the price elasticities from models that use data at different degrees of aggregation are attributable to the distribution of prices and income in the sample. Aggregating relies on a strong set of assumptions about

[8] Bohi (1993, p.33) further elaborates that "The importance of measurement and aggregation errors in the analysis of demand elasticities is a matter of speculation that can be evaluated only by a comparison of results obtained from different samples, collected from different sources and at various levels of aggregation."

homogeneity in terms of consumer preferences and price exposure; one cannot simply aggregate consumers who observe different prices and respond differently to price changes, and expect to find stable price elasticities.

Another reason for the difference in estimates between studies may lie in the covariates the model controls for. Specifications that control for energy-using capital are generally interpreted as proving short-run elasticities.[9] With panel data that lack information about capital stock, housing and equipment in the home, the assumption is sometimes made that these are approximately constant over time and are captured into household-, home- or meter-level fixed effects (Ito, 2014; Auffhammer, 2014).

3. Methods

Our research questions are summarized in Table 2. The ideal approach to answer most of them is to use one or more micro-level panel dataset(s) to estimate residential energy demand functions. Cross-sections extracted from such panels can be used to examine issue 1 in Table 2. We exploit the panels to test the effect of rising or falling prices on elasticity (item 2 in Table 2). We increase the level of geographic aggregation of the observation (e.g., to the city- or state-level) to get total demand or the demand for a representative consumer to study the extent of aggregation bias (item 3 in Table 2).

Comparisons between fixed-effects models and pooled-data specifications allow us to cast light on issues 4 (unobserved heterogeneity) and 5 (within variation in electricity prices and

[9] Dynamic models are also sometimes used to obtain long-run elasticities (Bernard et al., 2011; Paul et al., 2009; Dergiades and Tsoulfides, 2008; Maddala et al., 1997; Alberini and Filippini, 2011; Bernstein and Griffin, 2005; Alberini et al., 2011; Okajima and Okajima, 2013; Boogen et al, 2014). In these models, the long-run estimate is equal to the short-run elasticity (i.e., the coefficient on log price) divided by one minus the coefficient on the lagged dependent variable.

the associated identification issues) of Table 2. Instrumental variable estimation is used to explore the extent of endogeneity bias (issue 6), whereas more detailed specifications that control for household and dwelling characteristics and equipment are used to explore issue 7.

Throughout this paper, we fit a log-log demand function, namely:

(1) $$lnQ_t = \beta_0 + lnP_t^e\beta_1 + lnI_t\beta_2 + lnHDD_t\beta_3 + lnCDD_t\beta_4 + lnP_t^g\beta_5 + \boldsymbol{HH_t}\beta_6 + \boldsymbol{D_t}\beta_7 + \boldsymbol{C_t}\beta_8 + \varepsilon,$$

where *lnQ* refers the log quantity of electricity annually consumed in year *t; lnP*^{e} the log price per kilowatt hour (kWh); *lnI* the log household income; *lnHDD* and *lnCDD* the log heating and cooling degree days, respectively; and *lnP*^{g} the log price of natural gas per cubic foot (ft^3). The terms $\boldsymbol{HH}$, $\boldsymbol{D}$, and $\boldsymbol{C}$ denote vectors of household level characteristics, dwelling characteristics, and capital stock.

When we use the full panel of data, the equation further includes time fixed effects γ_t, as well as cross sectional-unit fixed effects $\delta_{i,}$ where *i* denotes the unit. The equation may be used to model the total consumption of a household (using the RECS or AHS) or housing unit (AHS), utility provider (EIA), city (AHS), or state (AHS, EIA). It is also possible to construct a "representative" consumer, such as the average consumer for a given utility in a given year.

We are unable to fit equation (1) with Forms EIA-861, which collect information from utilities and not from households. With these data, our model is

(2) $$lnQ_{it} = \beta_0 + lnP_{it}^e\beta_1 + lnHDD_{st}\beta_2 + lnCDD_{st}\beta_3 + lnP_{it}^g\beta_4 + \delta_i + \gamma_t + \varepsilon_{it},$$

where *i* denotes a utility provider. Note that *HDD* and *CDD* are available only at the level of the state *s*, but not at the utility service territory level.

4. Data

Candidate datasets for our analyses are micro-level, panel datasets that document energy usage and price,[10] and ideally user characteristics, with sufficient geographical coverage and over a sufficiently long study period. We have identified two such datasets—the AHS and the Forms EIA-861. Information about these two datasets is summarized in Table 3, and the AHS is described in detail in Alberini et al. (2011).

The AHS collects information from the household living at a specified residence every two years. The unit of observation is the home, not the household, and so when a household moves out of a home and is replaced by another, the AHS is administered to the latter. With this panel dataset, one can use fixed effects at the household or house level. House-specific fixed effects imply slightly longer panels than with household specific fixed effects.

In the AHS, information is collected about the dwelling structure, tenure and ownership, and associated costs (e.g., rent or mortgage payments), plus household sociodemographics, energy bills, heating and cooling and stock of energy-using appliances. Geographical identifiers are provided only if the household resides in a metropolitan area with 100,000 or more people, and so in this paper attention is focused on 55 metro areas across the US. We use the data from 1997 to 2009, and impute electricity prices at the city level to derive annual electricity consumption in kWh.

The Forms EIA-861 data are a panel. The cross-sectional unit is each utility, which reports sales and revenues for each year by class of customers. We use these data in a number of possible ways. For example, we use log total electricity consumed by its residential customers as

[10] In none of our three datasets do we have information on marginal price, so we are only able to measure price as an average. This is not ideal, as households are often subject to a block price schedule, so that price and consumption levels are endogenously determined. Shin (1985), however, argues that this distinction may not be so relevant, and that customers tend to respond to the average price anyway, since it can be directly calculated from the electricity bill, whereas the marginal price can be costly to determine.

the dependent variable in a regression that enters the log price (calculated as total revenue divided by total kWh consumption) and the log total number of consumers in the right-hand side. Another option is to create a "representative" customer. In this case, the dependent variable in our regression is log total electricity consumption divided by the number of residential customers. The log average price is still included in the right-hand side of the regression, but the log number of customers is omitted. For consistency with our AHS data, we use data from 1997 to 2009.

We also have a cross-sectional dataset—RECS—which provides information about a household's composition and stock of appliances, and reports electricity consumption at the annual level. We use 2009 only, as the public version of the survey from that year contains information sufficient to identify the location of households in 16 states,[11] whereas previous years identified the location for residents of only the four largest states (California, New York, Texas and Florida). The 2009 sample size is also much larger than any previous year.

A close comparison of the three datasets (see Table A.1 in the Appendix) suggests good comparability in terms of the variables of primary interest to us. In the year 2009, we find the average consumption per household to range between 11,302 and 12,815 kWh, and the average price of electricity to be 11 to 12 cents per kWh (in 2009 dollars).[12]

Among our household level datasets, RECS and AHS, in particular, we observe similar overall variation in consumption and prices. We also observe similar means and standard deviations for heating and cooling degree days. Other statistics, however, suggest interesting differences between the datasets. Single family homes in RECS, for example, are on average

[11] The sixteen states individually identified in RECS 2009 are Massachusetts, New York, New Jersey, Pennsylvania, Illinois, Michigan, Wisconsin, Missouri, Virginia, Georgia, Florida, Tennessee, Texas, Colorado, Arizona, and California.
[12] These statistics are based on samples that exclude the top and bottom 1% of the distribution of kWhs used. All regressions are based on such trimmed samples.

35% larger in terms of square footage. While the availability of air conditioning is similar across the two datasets, the fraction of homes which primarily rely on electricity for heating is higher in RECS (28%) than in AHS (24%). The geographic distribution of the samples is also different. In terms of Census Divisions, the AHS samples more heavily from the Mid-Atlantic, Midwest, West South Central, and Pacific divisions; whereas RECS places on more emphasis on the Northeast, West North Central, South Atlantic, and East South Central divisions. These differences are due to the combination of different sampling frames across the two surveys, plus the fact that we retain for our purposes only the AHS observations from metropolitan areas with over 100,000 people.

In terms of prices, in Figure 1 we plot the kernel density distribution of prices for observations in the year 2009 for each of our three datasets. We observe the smoothest distribution among the average prices from Forms EIA-861, followed by RECS, which has a somewhat longer upper tail. The price distribution for the AHS, in contrast, is quite “jagged” by comparison. These different distributions may explain the different price elasticities of demand when the data are aggregated to a coarser geographical level, as shown by Halvorsen and Larsen (2013) with data from Norway.

5. Results

A. The effect of timing and sample periods

We begin with item 1 from Table 2, by examining the sensitivity of price elasticity estimates to the sample period. To do so, we exploit the panel nature of the AHS and EIA datasets and create cross sections for each year, which we use in separate regressions. Price elasticities from the regressions for the AHS, and their 95% confidence intervals, are plotted in

Figure 2, and range from -0.83 to -0.55. This variation from one year to the next is consistent with that observed by Nesbakken (1999) for Norway in 1990, 1993, 1994, and 1995. Her energy price elasticities are -0.24, -0.57, -0.33 and -0.53, respectively.[13]

As a first check for the claim sometimes made in the literature that price elasticities are different when prices are rising or falling, we plot the elasticities against the average electricity price in each year in Figure 3. Figure 3 suggests an inverse relationship between elasticity and average price in that year. It is possible that this relationship is causal; households might be more sensitive to consumption changes when the share of their budget going to electricity is higher. Ultimately, however, it is difficult to say if price elasticities have systematically changed over time, given the fluctuations in the point estimates observed from year to year, the width of their confidence intervals, and the limited number of data points from which to draw inference.

Another reason why price elasticity estimates vary over the years might be the price variation in the data. For price elasticities to be reliably identified, sufficient variation in prices is needed to observe the extent to which consumption actually changes. We plot price elasticities against the cross-sectional variance in price in each year in Figure 4, which suggests a negative association. As price variance increases, the price elasticity appears to decrease in magnitude. Again, it is difficult to say if this is a credible finding, as the variances tend to be very small. However, the pattern in Figure 4 is broadly consistent with the notion that the larger the variation in price, the smaller – and closer to the bulk of the evidence from earlier studies[14] – the price elasticity.

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[13] Nesbakken (1999) uses a discrete-choice/continuous model where households choose their fuel combinations (e.g., electricity only, electricity plus heating oil, electricity plus gas, etc.) and total energy use a function of the fuel prices, housing characteristics and household sociodemographics. The model takes the equipment as given, but allows for substitution between fuels. Also see Nesbakken (2001).

[14] In 15 of the 22 studies (68%) listed in Table 1, the price elasticity was less than one in absolute value.

We perform the same exercise for the Forms EIA-861 data, using utility-level observations. The price elasticities, plotted in Figure 5, are relatively stable over time, although in this case they appear to be estimated imprecisely, as indicated by the wide ranges of the confidence intervals. This likely is due in part to the comparatively smaller sample sizes in each year.[15] In Figure 6, we again plot price elasticities of demand against prices. The relationship for the Forms EIA-861 data is the opposite of that seen in Figure 3 for the AHS data: the price elasticities appear to be smaller as the average price increases. This could be an artifact due to our construction of average prices from revenue and kWhs, or a signal that the utilities charge higher prices in places where the demand is less elastic.

In Figure 7, we again plot the annual price variance against price elasticities, for the Forms EIA-861 data. The pattern here is similar to that of Figure 4. It is worth noting that the variances in Figure 7 are lower than those in Figure 4, and this could be the reason for the high standard errors around the price elasticities from the Forms EIA-861 data.

For item 2 of Table 2, we test for asymmetry of price elasticities between periods of rising and declining prices by fitting fixed effects models on the original, full panel datasets and adding the log price interacted with a dummy variable denoting whether the price has risen or declined relative to the previous period.

Our approach differs from previous literature, which used country-level time-series data. Ryan et al. (1996) model price asymmetry by regressing fuel expenditure shares on the current period price, $ln(P_{j,t})$ (*j* referring here to commodity *j*), which is approximated by the decomposed

[15] While our AHS dataset boasts 4,738 to 11,180 observations per year, there are a maximum of 3,036 observations per year in the Forms EIA-861 data.

value $ln(P_{j,t-1}) + \frac{\Delta P^+}{P_{j,t-1}} + \frac{\Delta P^-}{P_{j,t-1}}$,[16] where ΔP_j^+ and ΔP_j^- respectively denote increases and decreases in prices. Alternatively, the approach used by Haas and Schipper (1998) and Gately and Huntington (2002) decomposes price for each time period *t* into four separate terms: 1) the log price during the very first period *t*=1, 2) the cumulative increases in log maximum price up to period *t*, 3) the cumulative increases in sub-maximum log price up to period *t*, and 4) the cumulative decreases in log price up to period *t*.

We opt for the dummy variable approach for two reasons. First, unlike Haas and Schipper (1998) and Gately and Huntington (2002), we do not have within year price variation. Second, the length of our panels is too short. With our data, the number of lagged prices per unit (house or utility) ranges from zero to six for the AHS, and zero to 12 for Forms EIA-861.

Our results for this exercise are summarized in Table 4. In the interest of space, in Table 4 we report only the coefficients for the two main price variables of interest—log price and log price interacted with the increasing-price dummy—which are reported in the first and second columns, respectively. The first four rows report the results for the AHS at different levels of aggregation: the first two are at the level of the household, with the first controlling for housing unit fixed effects and the second controlling for household fixed effects; the third and fourth are representative consumer models, where all quantities are aggregated at the metropolitan area- and state-levels, respectively. The final two rows report the results for representative consumer models using Forms EIA-861 at utility- and state-levels, respectively.

Column (2) of Table 4 shows that, in all cases, the coefficient on the interaction term of interest is very small. Only in half of the cases—with the AHS housing unit fixed effects model,

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[16] The full formula, which this term approximates for small changes in P, is $ln(P_{j,t}) = ln(P_{j,t-1}) + ln(1 + \frac{\Delta P_j}{P_{j,t-1}})$.

and the Forms EIA-861 utility- and state-level models—is the coefficient statistically significant at the conventional levels, and, even so, it remains practically insignificant.

Insufficient variation in “rising prices” does not appear to be a contributing factor to these results, as the third column in Table 4 suggests that rising prices account for between 45 percent and 73 percent of the observations. For both the AHS and Forms EIA-861 dataset, this proportion increases with the observations’ level of aggregation.

B. Aggregation

We next explore the issues of aggregation bias (item 3 of Table 2) by first estimating models using the household micro data from the AHS, and then by aggregating our observations to the levels of metropolitan area and state for the AHS. With the Forms EIA-861, we first fit models to the utility level sample and then at the state level sample. In each case, we consider both pooled data and fixed effects models. We begin by examining the results from Table 5a, which refers to representative consumer models for each level of aggregation. Again, in the interest of brevity, we only report the results for the price elasticity coefficient, β_1. The first two columns report the results for the AHS, the second two for Forms EIA-861.

For the AHS, using more aggregated observations produces a more inelastic demand. This applies whether or not we include fixed effects in the model. This pattern is consistent with that observed by Halvorsen and Larsen (2013), who find that price elasticity decreases when aggregated microdata or macrodata are used (in some cases, elasticities based on highly aggregated data were even positive). With the Forms EIA-861 data, however, aggregating the utility-level data to the state-level produces a higher price elasticity. In the case of the fixed effects models, the difference between the estimates of these two models is substantial—almost twofold. That we observe different results from the AHS and EIA datasets seems plausible. As noted by Halvorsen and Larsen (2013), the relationship between the level of aggregation and the price elasticity is not necessarily monotonic, as the effect of aggregation depends to a large extent on the distribution of prices and income among the population of interest.

In Table 5b, we fit similar models as in Table 5a, but this time the dependent variable is the aggregate amount of electricity consumed.[17] For example, if the unit of observation is the state, the dependent variable is the log of total consumption in the state. The model specifications are identical to those in Table 5a, except that we control for the log number of consumers.[18] In the case of the AHS, neither the city- nor state-level results change much compared to their counterparts in Table 5a. The Forms EIA-861 data displays similar results, except for the state fixed effects model. Here, the coefficient estimate of -0.146 at the state level is 20 percent lower than the coefficient of -0.203 for the same fixed effects model at utility level. This decreased elasticity with aggregation is now consistent with the pattern observed with the AHS.

C. Unobserved heterogeneity

Turning next to the effect of unobserved heterogeneity (item 4 of Table 2), we compare our pooled data models with their fixed effects counterparts. For simplicity, we comment on the results in Table 5a (the results in Table 5b are similar). For any given level of aggregation, consumers are more price inelastic when the model includes fixed effects. Aggregating the data increases the discrepancy between the pooled and fixed effects models. This effect is more pronounced with the AHS data. With the latter, the proportional change ranges from 14 percent

[17] The first two rows of Tables 5a and 5b are thus the same.
[18] The representative consumer model can be regarded as a special case, wherein the log number of consumers is alternatively included as an independent variable, and its coefficient is constrained to equaling one.

(household-level model and household fixed effects) to 34 percent (state-level representative consumer model). With Forms EIA-861, the decrease ranges from 40 percent, for the utility-level representative consumer model, to 71 percent, for the state level representative consumer model. One reason for our fixed effects results being more price inelastic might be the limited "within" variation: as shown in Table 6, the "between" variation in price across units always trumps the former. Another reason might be that omitting the fixed effects biases the price elasticities.

D. The effect of instrumental variable estimation

In the context of our analysis, instrumental variables (Item 6, Table 2) are justified for two reasons. First, they are used to address the endogeneity of price where block or two-part tariffs are present. Second, they are used to address measurement error in price. Measurement error is almost certainly present in our datasets, especially in the AHS, where we impute prices at the metropolitan area-level. In general, it is difficult to find good-quality instruments, since we do not have marginal prices or policy changes that might be regarded as exogenous shocks and are correlated with price changes.

In what follows, we use two different instruments: the first is the average price of electricity at the state level; the second is a cross-validation (CV) instrument, namely the average of one's neighbor's price. We reason that a given household's neighbors face a similar tariff structure as that household, but the prices they face cannot possibly cause this household's consumption. We use the state price as an instrument with all three datasets, and the CV as an instrument with RECS. The "neighbors" are all other households in the same state.[19]

[19] The CV instrument was also considered for Forms EIA-861 dataset. They are not included here, in the interest of brevity, as the results are shown to be similar to those using state-level prices as an instrument.

We begin with Panel A in Table 7, which displays the results for fixed effects models, using the AHS and Forms EIA-861 at levels of aggregation below the state. The first three rows refer to the AHS data, which are used with two different types of fixed effects (house and household fixed effects, respectively) and after aggregating them to the city level. The fourth and last row refers to the Forms 861, which are used at the utility level.

In rows 1-2, the IV model produces a lower price elasticity than OLS, but within at most 24 percent of the price elasticity from OLS or the within estimator. The results are qualitatively similar when we consider the results from representative consumer models aggregated at the city and utility level, as shown in the third and fourth rows of Panel A. In these cases, going from OLS to 2SLS changes the price elasticity estimate by 27 to 28 percent.

Should these findings be due to having poor quality instruments, we turn to the 2009 RECS, which allows us to experiment with both types of instruments. We display these results in Panel B of Table 7, where we consider two specifications—one with and one without controls for capital stock and equipment, which lead to short-run and long-run elasticities, respectively.

Overall, the results are similar across instruments, and indicate a larger, yet reasonable, change in the price elasticity when going from OLS to 2SLS. Unlike the AHS, this change is somewhat sensitive to the inclusion of capital stock in the model. For specifications with controls for capital stock and equipment, it ranges from 77 to 85 percent; for those without controls, 68 to 75 percent.[20]

[20] This change is in the coefficient is much smaller in our fixed effects models, partly because the fixed effects are absorbing the effect of the capital stock.

E. The effect of controlling for housing characteristics and capital stock

For our last question (item 7 of Table 2), we further examine the importance of controlling for housing characteristics and capital stock, when estimating price elasticity. Here, we focus exclusively on the RECS survey in 2009. Table 8 summarizes the results from four models. Column (1) consists of a basic household demand model, by controlling only for the log price, log household income, fixed effects at the level of the Census region, and log heating and cooling degree days; columns (2), (3), and (4) further control for household characteristics (log household members, and an indicator for home ownership), characteristics of the housing unit (age of home, the log square footage, etc.), and capital stock (ownership of electric heating, a central AC unit, and a window AC), respectively. Table 8 illustrates that adding both housing characteristics and capital stock decreases price elasticity. This is consistent with the notion that controlling for capital stock produces price elasticities that should be interpreted as short run. The effect is modest, however.

Importantly, Table 8 shows that controlling for these variables has a strong effect on income elasticity, which falls to nearly one third of the initial estimate – from 0.17 to 0.06. Higher household incomes are correlated with other regressors—the size of one's house, the possession of capital stock appliances, etc.—that have a direct effect on consumption.

6. Conclusions

An important question in energy economics and policy is how elastic demand is with respect to energy prices. This paper has examined residential electricity demand, and systematically checked the impact of various factors that observers have linked to price elasticity estimates.

We have worked with three micro-level datasets from the U.S. Two are at the household level (the AHS and RECS) and one at the utility level (Forms EIA-861). Two (the AHS and Forms EIA-861) are panel, whereas RECS is a cross section (repeated every four years). Consumption levels and prices can be aggregated (i.e., summed and averaged, respectively) over specified geographic areas, and it is possible to extract cross sections from the longitudinal datasets.

We do not find strong evidence of price elasticities systematically changing over time; estimate appear to fluctuate within a range of 35 percentage points. However, splitting our panel datasets into annual cross sections, we do observe a negative relationship between price elasticities and the price variance for that year. Whether prices are rising or falling appears to have little effect on our price elasticity estimates. We also find that aggregating our data generally produces lower price elasticity estimates, as does controlling for cross sectional unit fixed effects when using panel data. The latter finding may be attributable to limited within price variation, relative to the between price variation, and/or to bias resulting from the omission of fixed effects. We experiment with instrumental variables, finding that addressing price endogeneity (which is due to two-part o block tariffs, or measurement error) has a small but noticeable effect for each of our datasets, and appears to be largest in the case of RECS. Finally, we find that controlling for housing characteristics and capital stock makes a difference. Omitting these variables increases price elasticity.

In general, the three datasets we used produce price elasticities of demand ranging from -0.2 to -0.8, confirming the notion that household electricity demand is not very elastic. Changing the estimation technique, aggregating the data or selecting specific years from the panel dataset can double or halve the price elasticity, which remains below one. In other contexts and with other data, a 100% or 50% change in the price elasticities may result in elasticities of one or stronger. In other words, simple data manipulations, or a different model specification or estimation technique, may bring the researcher to conclude that the demand is elastic. This emphasizes the importance of awareness of the data geographical coverage and study period, and the need for extensive robustness checks, when estimating energy demand functions.

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Figure 1. Distribution of prices from each dataset, for year 2009

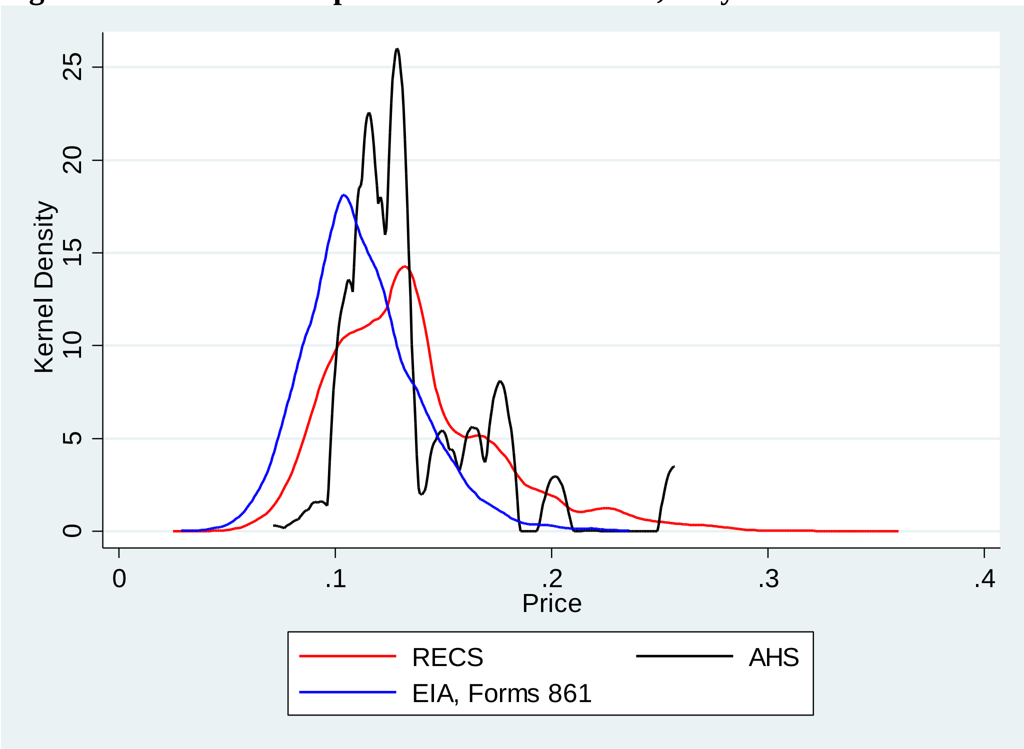
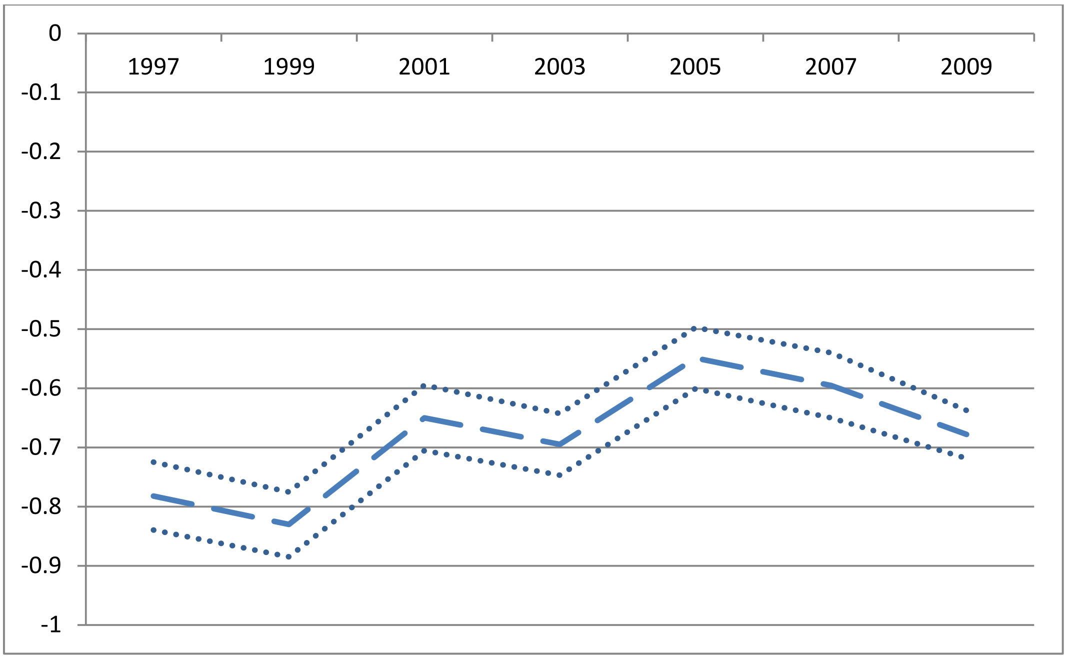


Figure 2. Price elasticities: the effect of using repeated cross sections to obtain yearly estimates (source: AHS, household level)



Note: estimates are provided with 95% confidence interval

Figure 3. Average yearly price plotted against price elasticity (Source: AHS)

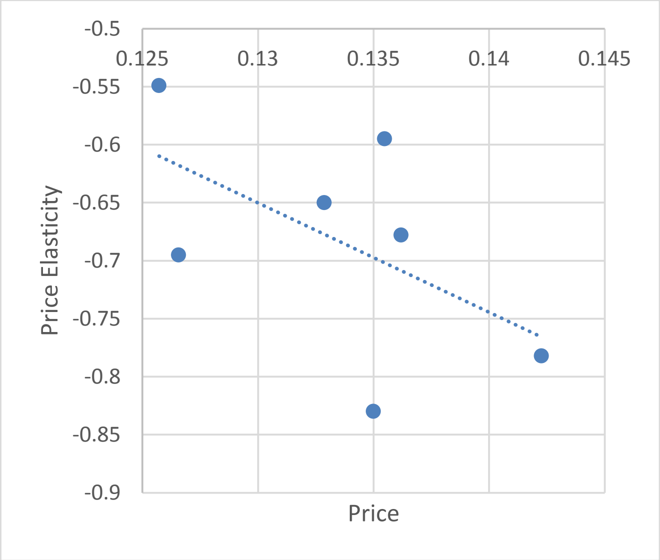


Figure 4. Yearly price variance plotted against price elasticity (Source: AHS)

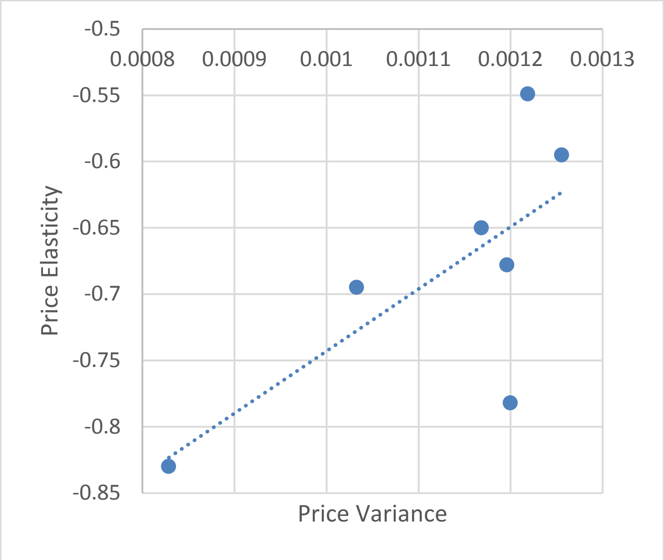
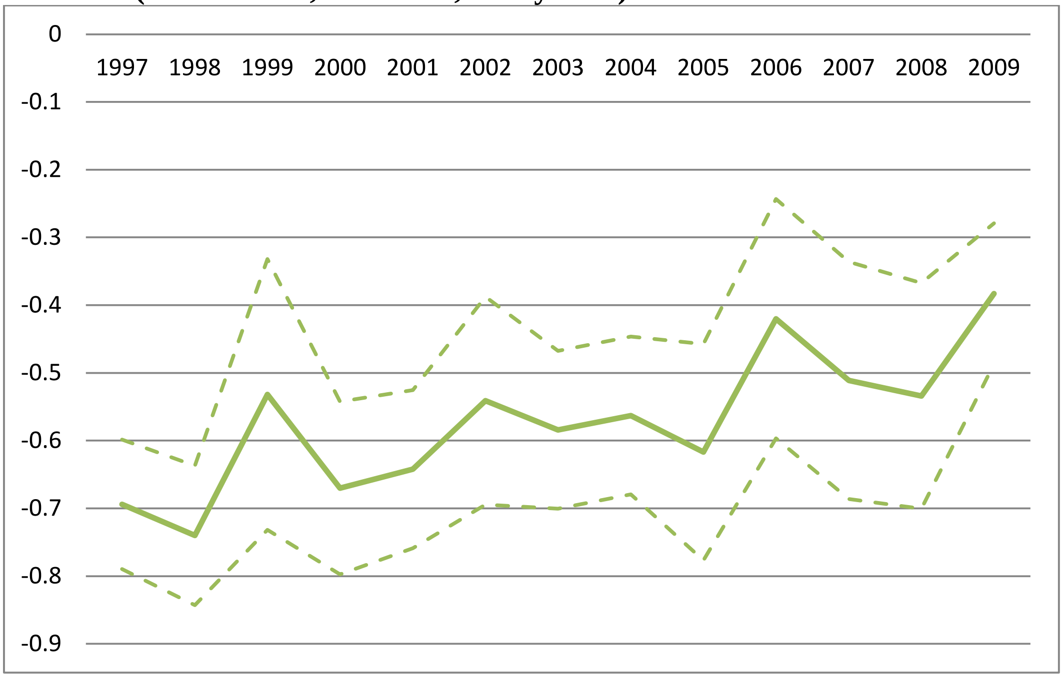


Figure 5. Price elasticities: the effect of using repeated cross sections to obtain yearly estimates (Source: EIA, Form 861, utility level)



Note: estimates are provided with 95% confidence interval

Figure 6. Average yearly price plotted against price elasticity (Source: EIA Forms 861)

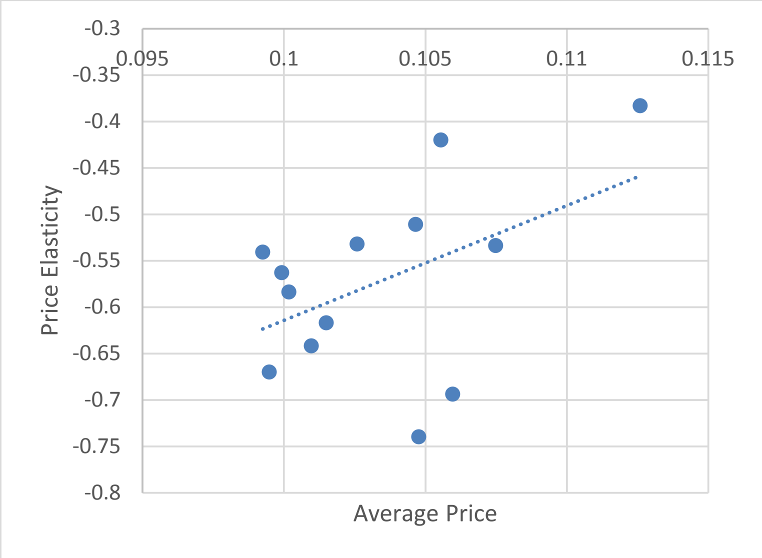


Figure 7. Yearly price variance plotted against price elasticity (Source: EIA Forms 861)

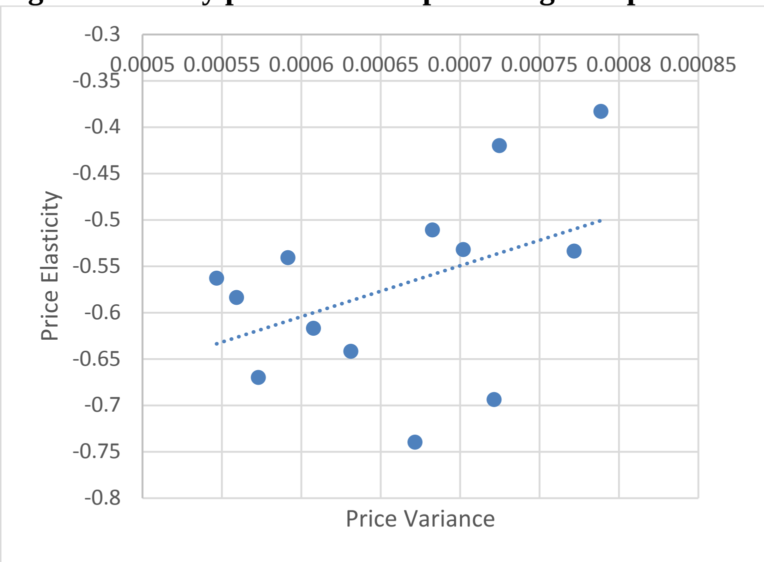


Table 1. Selected empirical studies and price elasticity estimates

Study	Type of data coverage	Variables included								Estimate(s) for fuel demand
		CI	I	P	lag	HH	S	C	O	
Quigley and Rubinfeld (1989)	Annual Housing Survey, cross section, 1980	x					x	x	x	−0.1 energy
Maddala et al. (1997)	State-level, panel data, 1970–1990	x	x	x	x					−0.19 to − 0.21 *short run* (− 0.56 to − 1.03 *long run*) electricity
Metcalf and Hasset (1999)	RECS household-level, rotating panel, 1984, 1987, and 1990	x	x	x		x	x	x		−0.78 to − 1.11 electricity
Garcia-Cerrutti (2000)	California county-level, panel data, 1983–1997	x	x	x						Long-run: −0.17 electricity
Kamerschen and Porter (2004)	Nationwide total, time series, 1973–1998	x	x	x					x	Long-run: −0.94 to − 0.85 electricity
Bernstein and Griffin (2005)	State-level, panel data, 1997–2004	x	x	x	x				x	−0.243 (− 0.32) electricity
Reiss and White (2005)	California RECS, household-level, multi-year cross sections, 1993 and 1997	x	x			x	x	x	x	−0.85 to − 1.02 electricity
Dergiades and Tsoulfidis (2008)	Nationwide total, time series, 1965–2006	x	x	x	x				x	−0.386 short-run (− 1.06 long-run) electricity
Borenstein (2009)	California Census block group-level, panel data, 2000-2006	x	x						x	-0.12 to 0 (marginal price); -0.95 to 0 (average price); -0.46 to 0.09 (expected marginal price)
Paul et al. (2009)	State-level, panel data, 1990–2006	x	x	x	x				x	−0.13 (− 0.36) electricity
Alberini and Filippini (2010)	State-level, panel data, 1995-2007	x	x	x	x	x				−0.15 to − 0.08 (− 0.78 to − 0.44) electricity
Ito (2014)	California household level, panel data, 1999-2008								x	−0.09 (marginal price); -0.12 to -0.11 (average price); -0.1 (expected marginal price)
Alberini et al. (2011)	AHS household-level, panel data, 1997,2007	x	x	x	x	x	x	x		−0.736 (−0.814) electricity
Fell et al. (2014)	CEX household-level, panel data, 2006-2008	x	x			x	x	x		−0.82 to − 1.02 electricity

Studies outside the U.S.										
Nesbakken (1999)	Norway household level, multi-year cross-sections, 1990, 1993,1994, 1995	x	x			x	x	x		-0.24 to -0.53 energy
Bernard et al. (2011)	Quebec household-level, cross-section, 1989–2002	x	x	x	x					−0.51 (− 1.32) electricity
Gans et al. (2013)	Ireland household level, cross section, 1991-2009	x	x			x	x	x		-0.93 to -0.44 electricity
Blazquez et al. (2013)	Spain province-level, panel data, 2000-2008	x	x		x	x			x	-0.07 (-0.19) electricity
Okajima and Okajima (2013)	Japan prefecture level, panel data, 1990-2007	x	x		x					−0.397 (−0.487) electricity
Krishnamurthy and Kriström (2013)	OECD household level, cross section, 2011		x			x	x	x		−1.25 to -1.18 (based on samples that use all of the countries covered by the study) electricity
Blazquez et al. (2013)	Spain province-level, panel data, 2001-2009	x	x						x	−0.09 to -0.06 electricity
Boogen et al. (2014)	Switzerland household level, cross section, 2005, 2011		x			x	x	x	x	-0.59 to -0.54 (-0.65 to -0.68) electricity

Notes: for variables included, the following acronyms are used: C, climate; I, income; P, price of other substitutes; Lag, lag terms for price and/or quantity; HH, household level information; S, housing structure information; C, capital stock; O, other information (e.g. time fixed effects)

Table 2. Summary of research questions

Issue	Data to be used	Methodology
1. Are price elasticity estimates influenced by the sample period?	AHS, Forms EIA-861	Produce and plot a series of cross sectional estimates for each year covered by each dataset
2. Are price elasticity estimates influenced by whether prices are rising or falling?	AHS (state level), Forms EIA-861 (state level)	Create a second variable which interacts price with an indicator for whether the price at the state level is higher or lower than in the previous year
3. Does aggregation bias price elasticity estimates?	AHS	Compare estimates obtained using the same data aggregated at the levels of household, city, and state
4. What is the effect of controlling for unobserved heterogeneity in panel datasets?	AHS, Forms EIA-861	Compare pooled-data and fixed-effects specifications
5. Variation in price: within and between variation	AHS, Forms EIA-861	Produce and compare summary statistics on prices
6. Endogeneity of price (due to measurement error, use of average or marginal price in the presence of block pricing or two-part tariffs, etc.)	RECS	Compare OLS with IV estimation
7. How sensitive are the elasticities to the inclusion of variables controlling for capital stock?	AHS, RECS	Compare specifications with and without such controls

Table 3. Description of datasets used

	Residential Energy Consumption Survey (RECS)	American Housing Survey (AHS)	Energy Information Agency (EIA), Forms EIA-861
Who collects the data	EIA	HUD	EIA
Data type	Repeated cross sections	rotating panel	panel
Geographic identifiers	State* or Census Division	Metropolitan Area (MSA)	State
Frequency of data collection	Every 4 years	Every two years (with some MSAs additionally surveyed in between)	Annual
Universe	US households	US homes	US electrical utilities
Number of cross-sectional units used in this paper	3,909	16.947 housing units, 23,011 households	6,972
Household characteristics available?	yes	yes	no
Structural characteristics of the home available?	yes	yes	no
Inventory and vintage of capital stock?	yes	major capital stock only; no vintage	no
Energy consumption data	total annual household electricity consumption (kWh), and total cost paid ($)	total annual household cost ($). Electricity consumption derived by dividing through price.	total annual sales (kWh) and revenue ($)
Endogeneity concerns for energy price variable	Measurement error due to use of average price; also, block pricing makes consumption correlated with price	Measurement error due to the use of average price, which is measured using the price of the utility provider associated with household's MSA	Measurement error due to use of average price; also, block pricing makes consumption correlated with price

*For 16 largest in 2009; for years prior to then, only for CA, FL, NY, and TX

Table 4. Price elasticities: the effect of controlling for rising/declining prices

		(1)	(2)	(3)
Dataset	Cross sectional unit	Log price (per kwh)	Log price x Dummy variable (equals 1 if average price exceeds previous period's)	Proportion of sample with dummy variable equal to 1
AHS	Housing unit	-0.591***	0.00599*	0.45
		(0.0482)	(0.00362)	
AHS	Household	-0.663***	0.00227	0.45
		(0.0524)	(0.00383)	
AHS	City	-0.390***	0.00655	0.5
		(0.0905)	(0.00755)	
AHS	State	-0.345***	0.00819	0.7
		(0.102)	(0.00934)	
Forms EIA-861	Utility	-0.214***	-0.00240***	0.43
		(0.0125)	(0.000439)	
Forms EIA-861	State	-0.323***	-0.00375*	0.73
		(0.0237)	(0.00198)	

Notes: robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; all models are aggregated at, and include fixed effects for, the level specified in parentheses. For the AHS, the previous period price is the average price from the previous time surveyed, two years prior; for the EIA, the previous period is one year prior.

Table 5a. Price elasticities: the effect of controlling for unobserved heterogeneity - Representative consumer model (Dependent variable: log kWh per consumer)

	American Housing Survey			EIA Forms 861		
Aggregated to…	Pooled data model	Fixed effects model		Pooled data model	Fixed effects model	
Household level	-0.729*** (0.0142)	-0.593*** (0.0301)	(dwelling fixed effects)			
Household level	-0.729*** (0.0142)	-0.623*** (0.0337)	(household fixed effects)			
Utility level				-0.308*** (0.00647)	-0.201*** (0.0116)	(utility fixed effects)
City level	-0.671*** (0.0575)	-0.455*** (0.0785)	(city fixed effects)			
State level	-0.554*** (0.0776)	-0.366*** (0.0846)	(state fixed effects)	-0.754*** (0.0349)	-0.359*** (0.0268)	(state fixed effects)

Notes: robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; to allow for comparability between datasets, control variables consist only of Census Division fixed effects and heating/cooling degree days; in these models, the dependent variable is the log average kWh consumed per consumer

Table 5b. Price elasticities: the effect of controlling for unobserved heterogeneity - Aggregated model (Dependent variable: log kWh)

	American Housing Survey			EIA Forms 861		
Aggregated to…	Pooled data model	Fixed effects model		Pooled data model	Fixed effects model	
Household level	-0.729*** (0.0142)	-0.593*** (0.0301)	(dwelling fixed effects)			
Household level	-0.729*** (0.0142)	-0.623*** (0.0337)	(household fixed effects)			
Utility level				-0.323*** (0.00648)	-0.203*** (0.0114)	(utility fixed effects)
City level	-0.667*** (0.0565)	-0.459*** (0.0777)	(city fixed effects)			
State level	-0.619*** (0.0848)	-0.367*** (0.0847)	(state fixed effects)	-0.724*** (0.110)	-0.146*** (0.0200)	(state fixed effects)

Notes: robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; to allow for comparability between datasets, control variables consist only of Census Division fixed effects and heating/cooling degree days; in these models, the dependent variable is the log aggregated kWh consumed

Table 6. Summary statistics for price, compared within and between datasets

Dataset	Cross sectional unit	Years	Mean	S.D., overall	S.D., between	S.D., within
AHS	Housing unit	1997-2009, biennially	0.1333	0.0338	0.0324	0.0106
AHS	Household	1997-2009, biennially	0.1333	0.0338	0.0326	0.0092
AHS	City	1997-2009, biennially	0.1170	0.0377	0.0360	0.0119
AHS	State	1997-2009, biennially	0.0981	0.0300	0.0256	0.0163
Forms EIA-861	Utility	1997-2009	0.1053	0.0264	0.0254	0.0106
Forms EIA-861	State	1997-2009	0.0954	0.0277	0.0226	0.0162

Table 7. Price elasticities: the effect of using instrumental variables (IV)

	OLS	IV
Panel A. Panel data, using fixed effect models at the level specified in parentheses		
AHS - (household level with housing unit fixed effects)	-0.590***	-0.456***
	(0.0301)	(0.0404)
AHS - (household level with household fixed effects)	-0.623***	-0.498***
	(0.0337)	(0.0444)
AHS (aggregated to city level)	-0.456***	-0.333***
	(0.0784)	(0.110)
Form 861 (utility level)	-0.201***	-0.259***
	(0.0116)	(0.0163)
Panel B. Cross sectional data		
RECS – controlling for capital stock and equipment (2009, IV=avg state price)	-0.356***	-0.658***
	(0.0310)	(0.0471)
RECS – controlling for capital stock and equipment (2009, IV=CV estimate)	-0.356***	-0.631***
	(0.0310)	(0.0452)
RECS – no capital stock and equipment controls (2009, IV=avg state price)	-0.437***	-0.764***
	(0.0324)	(0.0494)
RECS – no capital stock and equipment controls (2009, IV=CV estimate)	-0.437***	-0.733***
	(0.0324)	(0.0471)

Notes: robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; variables relating to capital stock include the possession of a central AC unit, window AC unit, and electric heating unit; for all specifications - except for RECS "CV" estimates - the instrumental variable used consists of the average price calculated at the state level, using the data from Form 861; for RECS, results are confined to 16 states, as residents from only those areas are identified at the state level; "CV" refers to "cross validation", whereby the instrument is constructed by taking the average price of all other households within the same state; results reported at the utility and city level are for representative consumer models (results using aggregated models are qualitatively similar).

Table 8. Price elasticities: the effect of controlling for household and dwelling characteristics, and appliance stock (Source: RECS, year 2009)

	(1)	(2)	(3)	(4)
log electricity price	-0.437***	-0.480***	-0.437***	-0.356***
	(0.0349)	(0.0324)	(0.0310)	(0.0308)
log household income	0.172***	0.122***	0.0622***	0.0556***
	(0.0115)	(0.0106)	(0.00958)	(0.00930)
Includes…				
region fixed effects	yes	yes	yes	yes
heating and cooling degree days	yes	yes	yes	yes
household characteristics	no	yes	yes	yes
housing characteristics	no	no	yes	yes
capital stock	no	no	no	yes

Notes: robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; "household characteristics" refers to the inclusion of controls for the log number of household members and a dummy variable for home ownership; "housing characteristics" refers to controls relating to the structure of the home; "capital stock" refers to controls for the ownership of an electric heating unit and both window and central air conditioning units.

Appendix

Appendix Table A.1 Summary statistics for the three data sources (RECS, AHS, Form 861); year 2009 only

Panel A. Number of cross sectional units

RECS	AHS	Form 861
8230	11178	2850

Panel B. Annual electricity consumption per household (kWh)

	mean	s.d.	min	max
RECS	12383.45	6764.449	2099	37411
AHS	12815.49	7184.008	1795.538	38895.37
Form 861	11301.75	3084.715	5045.915	21474.23

Panel C. Average price of electricity per kWh (2009 $)

	mean	s.d.	min	max
RECS	0.124167	0.035474	0.023041	0.330586
AHS	0.124928	0.031711	0.065446	0.235759
Form 861	0.114065	0.026255	0.026428	0.216412

Panel D. Average square footage of home

	mean	s.d.	min	max
RECS	2606.209	1338.149	409	9808
AHS	1924.698	1037.305	400	10000

Panel E. Ownership of capital stock

	AC		Electric heating	
	mean	s.d.	mean	s.d.
RECS	0.848846	0.358221	0.282746	0.450361
AHS	0.838969	0.367576	0.238504	0.426188

Panel F. Climate

	Heating degree days				Cooling degree days			
	mean	s.d.	min	max	mean	s.d.	min	max
RECS	4235.202	2297.988	6	11933	1393.657	1104.957	0	5480
AHS	3921.736	2289.243	140.175	8197.99	1411.125	1203.497	57.11429	5001.523

Panel G. Geographic distribution (%)

	AHS	RECS
CT,MA,ME,NH,RI,VT	1.79	6.95
NJ,NY,PA	14.47	9.39
IL,IN,MI,OH,WI	22.31	10.46
IA,KS,MN,MO,ND,NE,SD	1.62	15.94
DC,DE,FL,GA,MD,NC,SC,VA,WV	6.97	18.51
AL,KY,MS,TN	0.98	5.69
AR,LA,OK,TX	22.29	10.49
CO,ID,MT,UT,WY,AZ,NM,NV	4.83	7.00
AK,CA,HI,OR,WA	24.74	15.58

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