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Residential consumption of gas and electricity in the U.S.: The role of prices and income

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ABSTRACT

We study the residential demand for electricity and gas, working with nationwide household-level data that cover recent years, namely 1997–2007. Our dataset is a mixed panel/multi-year cross-sections of dwellings/households in the 50 largest metropolitan areas in the United States as of 2008. We estimate static and dynamic models of electricity and gas demand. We find strong household response to energy prices, both in the short and long term. From the static models, we get estimates of the own price elasticity of electricity demand in the −0.860 to −0.667 range, while the own price elasticity of gas demand is −0.693 to −0.566. These results are robust to a variety of checks. Contrary to earlier literature (Metcalf and Hassett, 1999; Reiss and White, 2005), we find no evidence of significantly different elasticities across households with electric and gas heat. The price elasticity of electricity demand declines with income, but the magnitude of this effect is small. These results are in sharp contrast to much of the literature on residential energy consumption in the United States, and with the figures used in current government agency practice. Our results suggest that there might be greater potential for policies which affect energy price than may have been previously appreciated.

1. Introduction

In the United States and in other developed countries, buildings account for over 40% of total annual energy use. Despite many recent policies that either mandate or promote energy efficiency among residential energy users,[1] U.S. residential energy demand has grown over the last three decades, and projections suggest that it will continue to do so for the foreseeable future (Energy Information Agency, 2010).

Recently, there has been considerable debate in academic and policy circles as to whether retail energy prices, including those charged to the residential sector, will increase or decrease as a result of deregulation (Fabrizio et al., 2007; Showalter, 2007a,b; Carlson and Loomis, 2008), establishment of emissions trading markets (e.g., Frondel et al., 2008; Burtraw et al., 2002; Smale et al., 2006), and imposition of renewable portfolio standards, which is usually done at the state level (Fischer, 2010). More stringent environmental regulations on emissions and pollutants from power plants (e.g., nitrogen and sulfur oxides, and mercury) and tightened ambient air quality standards are also expected to increase the cost of energy to consumers.[2]

For the purpose of forecasting demand and planning for generation, transmission and distribution capacity, and for energy policy purposes, it is important to measure the responsiveness of residential

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[1] The American Recovery and Reinvestment Act (the Stimulus Bill) of 2009, for instance, allocated some $27.2 Billion for energy efficiency and renewable energy R&D. Yet, despite many cost-effective opportunities for energy efficiency improvement, projects often go unpursued. In principle, were homeowners aware of the future energy savings, they would spontaneously undertake energy efficiency investments in their homes. In practice, consumers and homeowners have often been observed to pass up opportunities to make energy-efficiency investments. Possible explanations for the so-called "energy paradox" (Jaffe and Stavins, 1994) include liquidity constraints, limited information, uncertainty about future energy prices (Hassett and Metcalf, 1993), high rates of intertemporal preferences, disbelief in engineering estimates of the cost savings themselves (Metcalf and Hassett, 1999), and institutional disincentives (see Golove and Eto, 1996).

[2] Financing costs from investments to electricity transmission and distribution infrastructure, volatility and rising scarcity in feedstocks such as coal, propane, natural gas, and petroleum, and the establishment of a price on carbon, are all possible mechanisms which would increase the price of energy (Basheda et al., 2006).

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Table 1
Selected empirical studies and price elasticity estimates.

Study	Type of data coverage	Estimate, fuel demand
Dergiades and Tsoulfidis (2008)	Nationwide total, time series, 1965–2006	−0.386 *short-run* (−1.06 *long-run*) electricity
Kamerschen and Porter (2004)	Nationwide total, time series, 1973–1998	Long-run: −0.94 to −0.85 electricity
Alberini and Filippini (2010)	State-level, panel data, 1995–2007	−0.15 to −0.08 (−0.78 to −0.44) electricity
Bernstein and Griffin (2005)	State-level, panel data, 1997–2004	−0.243 (−0.32) electricity
Paul et al. (2009)	State-level, panel data, 1990–2006	−0.13 (−0.36) electricity
Maddala et al. (1997)	State-level, panel data, 1970–1990	−0.19 to −0.21 (−0.56 to −1.03) electricity −0.09 to −0.18 (0.24 to −1.36) gas
Garcia-Cerrutti (2000)	California county-level, panel data, 1983–1997	Long-run: −0.17 electricity; −0.11 gas
Quigley and Rubinfeld (1989)	AHS household-level, cross section, 1980	−0.1 energy
Fell et al. (2010)	CEX and RECS household-level, 2004–2006	−0.82 to −1.02 electricity
Metcalf and Hassett (1999)	RECS household-level, panel data, 1984, 1987 and 1990	−0.78 to −1.11 electricity; −0.48 to −0.71 gas
Reiss and White (2005)	California RECS, household-level, multi-year cross sections, 1993 and 1997	−0.85 to −1.02 electricity
Studies outside the U.S.		
Meier and Rehdanz (2010)	UK, household-level, panel data, 1991–2005	−0.4 to −0.49 oil −0.34 to −0.56 gas
Rehdanz (2007)	Germany household-level panel, 1998 and 2003	−2.03 to−1.68 oil; −0.63 to −0.44 gas
Leth-Petersen and Togeby (2001)	Denmark panel data, 1984–995	−0.08 oil; −0.02 district heating
Bernard et al. (2010)	Quebec household-level, multi-year cross-sections, 1989–2002	−0.51 (−1.32) electricity
Nesbakken (1999)	Norway household level, multi-year cross-sections, 1990–1992, 1994–1995	−0.33 (−0.66) electricity

energy demand to the prices of electricity and gas, the two major sources of residential energy in the U.S. Earlier research has examined household demand for energy and its responsiveness to price, but these analyses i) used old data (Quigley and Rubinfeld, 1989; Metcalf and Hassett, 1999), ii) are restricted to limited geographical areas (e.g., Garcia-Cerrutti, 2000; Reiss and White, 2005), so that it is difficult to extrapolate their results to other areas with different climates, housing stock and electricity suppliers, or iii) were based on cross-sections or extremely short panels of data (with a maximum of two observations per household) (e.g., Metcalf and Hassett, 1999), and did not fully address issues of unobserved heterogeneity and endogeneity. In some cases, responsiveness to price was inferred from supply shocks so severe and geographically circumscribed (e.g., Bushnell and Mansur, 2005; Reiss and White, 2008) as to render them inapplicable for broader areas and more gradual price changes.

For these reasons, in this paper we wish to ask three research questions. First, what *are* the (nationwide) price elasticities of residential electricity and gas demand? Second, is such responsiveness sensitive to equipment and energy choices that are not easily reversed (e.g., using gas or electricity for heating or cooling)? Third, how does household income influence demand and the price elasticities?

We use energy utility data for over 69,000 single-family homes and duplexes (74,000 households) in the 50 largest metropolitan areas in the US for 1997–2007, and estimate static and dynamic models, with and without controls for the current stock of appliances. Unobserved heterogeneity is accounted for using fixed effects at various levels (at the city, dwelling and dwelling-household level). Briefly, we find that electricity use is responsive to the price of electricity (with an elasticity that ranges from −0.67 to −0.86) and increases with the price of gas, indicating that the latter is a substitute for electricity. The demand for gas is only slightly less responsive, with own-price elasticities ranging from −0.565 to −0.693. The elasticities are highest in the models with city-specific effects, and lowest in the models with dwelling-specific effects, but stay within a limited range. (Accounting for unobserved heterogeneity reduces the elasticities by 15% to 32% relative to a model that does not include any effects at all, where the own price elasticity of electricity demand is −1.).

The price elasticities are stable across specifications, and similar for homes with electric and gas heat. Our checks suggest that the effect of mismeasuring energy prices is small. The price elasticities are slightly higher among the poorest households (those that fall in the bottom 25% of the distribution of household income in our sample), and decline monotonically with income, but in practice this effect is not important. Our dynamic models produce short-run own-price elasticities equal to −0.736 and −0.572 for electricity and gas, respectively. Their long-run counterparts are −0.814 and −0.647, respectively. These figures are virtually unchanged whether or not we control for difficult-to-reverse choices of heating/cooling technologies.

The remainder of the paper is organized as follows. We offer a brief literature review in Section 2. We describe the models and econometric issues in Section 3 and the data in Section 4. Section 5 presents the results, and Section 6 offers concluding remarks.

2. Previous literature

Knowing the responsiveness of energy demand to the price allows analysts to predict the effects of price changes or policies that result in price changes—for example, taxes on carbon emissions, or mandates on the share of renewable energy. Earlier research has produced a wide range of estimates of the price elasticity of demand in the residential sector, possibly because of the diverse types of data used (time-series, cross-sections and panel), level of geographical and jurisdictional aggregation (local, state, or national), extent of the observed variation in price, and time periods covered.

We summarize selected studies in Table 1. These include studies based on annual time-series aggregates for the entire US, such as Dergiades and Tsoulfidis (2008), who estimate the short- (long-) run own-price elasticity of residential electricity consumption to be −0.386 (−1.06), and Kamerschen and Porter (2004), where the elasticities range from −0.94 to −0.85. Studies based on recent state-level panel data, such as Bernstein and Griffin (2005), Paul et al. (2009), and Alberini and Filippini (2010), have often found that the demand is relatively insensitive to price, at least in the short term, and that the estimates of the long-run elasticity are very sensitive to the specific estimation procedure.[3] Garcia-Cerrutti (2000) uses county-

[3] For example, Alberini and Filippini (2010) use annual state-level data in the U.S. from 1995 to 2007, and attempt to get consistent estimates of the long-run elasticity by using a bias correct “within” estimator (Kiviet, 1995) and the Blundell and Bond (1998) approach. The short-run own price elasticities of electricity range from −0.15 to −0.08, and their long-run counterparts range from −0.78 to −0.44.

level data from 44 California counties for 1983–1997, estimates the own-price elasticity of electricity demand to be −0.17 in the short run and −0.19 in the long run, and uncovers significant variation between counties.

Most household-level data studies are limited in either time coverage or geographic scale. Quigley and Rubinfeld (1989) use a cross-section from the 1980 American Housing Survey and find evidence of low elasticity of energy demand (−0.1 in the short run). Metcalf and Hassett (1999) use the 1984, 1987 and 1990 waves of the Department of Energy's Residential Energy Consumption Survey (RECS) to examine homeowners' insulation investments, finding price elasticities of electricity ranging from −0.73 to −1.16.

Bernard et al. (2010) have multi-year cross-sections about electricity and gas consumption and prices in Quebec from 1989 to 2002, estimate the short-run and long-run elasticity to be −0.51 and −1.32, respectively, and conclude that electricity and natural gas are substitutes.[4] Reiss and White (2005) focus on the California households in RECS, match each household with the block pricing structure applied by the utility that serves each area, and estimate a model of choice of block and consumption levels using GMM.

One concern when examining the responsiveness of electricity use with respect to price is that the data contain sufficient price variation. Such variation is usually attained by selecting a broad geographic area and/or a sufficient long period of time. In some cases, identification is made possible by abrupt changes in prices due to supply conditions. Reiss and White (2008) and Bushnell and Mansur (2005) exploit the energy crisis and rapidly growing electricity rates in California in 2000 and 2001, and document relatively large reductions in energy usage induced by such price increases. Haas and Schipper (1998) argue that energy-saving investments spurred by raising prices are likely to remain in place even in periods of declining energy prices, but in practice there is reason to question the external validity of findings based on unusual market circumstances at specific locations.

In this paper, we avoid these concerns by following a nationwide sample of dwellings over ten years, and augmenting these data with multi-year cross-sections of households from the same metropolitan areas. To conduct our analyses, we must assign the correct energy price to each household, but doing so is not straightforward.

There is considerable debate in the literature whether household energy demand depends on the marginal or average price, which may differ in the presence of fixed fee and block pricing. Shin (1985) argues that households will respond to average price, which is easily calculated from the electricity bill, rather than to the actual block marginal price, which is costly to determine, and develops an empirical strategy for testing this conjecture. The average price is also used in Metcalf and Hassett (1999),[5] and Borenstein (2008, 2009) and Ito (2010) find no evidence that consumers "bunching up" around the block where the price changes, as one would expect if consumers truly respond to marginal price. If demand is assumed to depend on the marginal block price, then price and consumption are simultaneously determined, and instrumental variable estimation techniques must be used (Burtless and Hausman, 1978; McFadden et al., 1978; Wilder and Willenborg, 1975; Hewitt and Hanemann, 1995; Reiss and White, 2005).

For lack of exact information about the block rates faced by the consumers, however, we are forced to use average price. We impute to each household the average price per unit of electricity or gas charged by the utilities in the area. This measure of price is exogenous to the household, but is affected by measurement error. We discuss this issue in Section 3.3 below. An additional concern is whether usage decisions depend on the price in the current (billing) period, on that of earlier periods, or a moving average of the prices of recent periods (Poyer and Williams, 1993). For good measure, in what follows we experiment with current price, as well as price of the previous period.

3. The models and econometric estimation issues

3.1. Two models of residential energy demand

In this paper, we focus on the demand for gas and electricity, because they are the most important fuels used by households in the U.S. Electricity is used by virtually 100% of the households, and gas serves 60% of the households. Fuel oil (7% of the households), LPG (1.5%) and kerosene (1.5%) are less important.[6]

We estimate two sets of models. In the first set, our regression equations are variants of the static energy demand model:

$$\ln Q_{it}^{(j)} = \beta_0^{(j)} + \beta_1^{(j)} \ln P_{E,it} + \beta_2^{(j)} \ln P_{G,it} + \mathbf{x}_{it}\boldsymbol{\gamma}^{(j)} + \tau_t + \varepsilon_{it}^{(j)} \qquad (1)$$

where j = E, G for electricity and gas, respectively, i denotes the dwelling, and t denotes the time period. Q is consumption, P denotes price, and the coefficients on the log prices are the short-term own- and cross-price elasticities.

Vector $\mathbf{x}$ is comprised of dwelling and household characteristics thought to influence the consumption of energy, such as weather, size and age of the home, heating and cooling equipment dummies, and appliances. For example, a house heated only with an electric heater would have a higher electricity demand than an identical home with gas heat. Household characteristics included in $\mathbf{x}$ are the number and age of occupants, income, the presence of children or elderly persons,[7] and a homeownership dummy. Eq. (1) includes year effects (the τs), and is easily amended to include dwelling or city-specific effects to account for unobserved heterogeneity.[8]

It is of interest to assess how consumption changes if individuals are allowed to adjust their stock of appliances and make energy efficiency and conservation investments. A partial-adjustment model (Houthakker, 1980) lets individuals adjust their stock of appliances and energy-efficiency investments. This model assumes that the change in log actual demand between any two periods ($t-1$ and t) is only some fraction (λ) of the difference between log actual demand in

[4] Studies outside of North America tend to be produce price elasticity ranges similar to those for North America. Nesbakken (1999) focuses on the choice of heating and residential energy consumption in Norway, reporting that short- and long-term price elasticities (in the range of −0.33 to −0.66) are remarkably stable across the 1990–1995 period, with the only exception of 1993. In contrast to other papers, responsiveness to price is more pronounced at higher levels of income. Rehdanz (2007) examines expenditures for residential space heating in Germany, and Meier and Rehdanz (2010) use a 15-year panel of residential heating expenditures in Great Britain. Using a log-linear specification with year and regional effects, they obtain gas price elasticities between −0.4 and −0.49, which fall in the range of −0.2 to −0.57 from the comparable literature. They obtain different elasticities for homeowners and renters. Leth-Petersen and Togeby (2001) find much lower price elasticities in heating fuels (on the order of −0.1) based on a panel dataset from Denmark and a conditional logit fixed-effect model.

[5] When the average price is computed from the consumer's bill divided by quantity, as is the case in Metcalf and Hassett (1999), it is endogenous with quantity.

[6] EIA, http://tonto.eia.doe.gov/energyexplained/index.cfm?page=us_energy_homes (last accessed 28 Sept. 2010).

[7] Earlier literature has examined the effect of age, race and ethnicity on energy demand. Poyer and Williams (1993) find that while the demand is inelastic for all groups, blacks appear to be more sensitive to short-run price variations than Hispanics and whites. Liao and Chang (2002) find that the elderly require more natural gas and fuel oil but less electricity, the demand for space heating increases as the elderly get older, and the demand for energy for heating water decreases with age.

[8] A special case of this situation is when the dwelling-specific effects are suppressed, but the error terms in the demand for electricity and gas equations are correlated within the same dwelling unit in the same period (but uncorrelated in different period and across dwellings). If so, the equations for log $Q^{(E)}$ and log $Q^{(G)}$ are part of a system of seemingly unrelated regression equation. Since the regressors are the same in the equations for log electricity and gas consumption, the most efficient estimation technique (GLS) is simplified to OLS applied separately to each equation.

period $t-1$ and the log of the long-run equilibrium demand in period t, Q_t^*. Formally,

$$\ln Q_t - \ln Q_{t-1} = \lambda(\ln Q_t^* - \ln Q_{t-1}), \quad (2)$$

where $0<\lambda<1$. The dwelling subscript i and the electricity or gas equation superscript j are omitted to avoid clutter. This implies that given an optimum, but unobservable, level of energy consumption, demand only gradually converges towards that optimum level between any two time periods.

Assume that desired energy use (for example, desired electricity consumption) can be expressed as $Q_t^* = \alpha \cdot P_E^\eta \cdot P_G^\theta \cdot \exp(\mathbf{x\gamma})$, where η and θ are the long-term elasticities with respect to the price of the electricity and that of gas, and $\mathbf{x}$ is the vector of variables influencing demand for energy, including income, climate, characteristics of the stock of housing, income, etc. On inserting this expression into Eq. (2), we get

$$\ln Q_t - \ln Q_{t-1} = \lambda \ln \alpha + \lambda\eta \ln P_E + \lambda\theta \ln P_G + \lambda\mathbf{x\gamma} - \lambda \ln Q_{t-1}. \quad (3)$$

On re-arranging and appending an econometric error term, we obtain the regression equation:

$$\ln Q_t = \lambda \ln \alpha + \lambda\eta \ln P_E + \lambda\theta \ln P_G + \mathbf{x}\lambda\boldsymbol{\gamma} + (1-\lambda) \ln Q_{t-1} + \varepsilon \quad (4)$$

Eq. (4) shows that the short-run elasticities are the regression coefficients on the log prices, whereas the long-run elasticities can be computed by dividing these short-run elasticities (i.e., the coefficients on the log prices) by the estimate of λ. In turn, the latter is easily obtained as 1 minus the coefficient on $\ln Q_{t-1}$.

3.2. Estimation of the dynamic model

We wish to estimate the partial adjustment model (Eq. (4)) with fixed, dwelling-specific effects. One concern with this specification is that the lagged dependent variable in the right-hand side may be serially correlated and hence correlated with the error term, which makes the LSDV and GLS estimators biased and inconsistent, since $\left(y_{i,t-1} - \overline{y}_{i,-1}\right)$, where $y_{i,t-1} = \ln Q_{i,t-1}$ and $\overline{y}_{i,-1}$ is the average of the $y_{i,t-1}$s for unit i, is correlated with $\left(\varepsilon_{i,t} - \overline{\varepsilon}_i\right)$ (see Baltagi, 2001). The bias vanishes as T gets large, but the LSDV estimator remains biased and inconsistent for N large and T small, as is the case here, since we have tens of thousands of homes but the maximum length of the longitudinal component of the sample is 6.[9]

Kiviet (1995) derives an approximation for the bias of the LSDV estimator when the errors are serially uncorrelated and the regressors are strongly exogenous, and proposes an estimator that is derived by subtracting a consistent estimate of this bias from the LSDV estimator. An alternative approach is to first-difference the data, thus swiping out the state-specific effects:

$$\Delta y_{it} = \gamma \cdot \Delta y_{i,t-1} + \Delta \mathbf{w}_{it}\boldsymbol{\beta} + \Delta\varepsilon_{it} \quad (5)$$

where $\mathbf{w}$ denotes all exogenous regressors in the right-hand side of Eq. (4), and to use $y_{i,t-2}$ and Δw_{it} as instruments for $\Delta y_{i,t-1}$ (Anderson and Hsiao, 1982).

Arellano and Bond (1991) point out that the latter approach is inefficient and argue that additional instruments can be obtained by exploiting the orthogonality conditions that exist between the lagged values of $y_{i,t}$ and the disturbances. The Arellano–Bond procedure is a generalized method of moments (GMM) estimator that is implemented in two steps. In practice, the Arellano–Bond estimator has been shown to be biased in small samples, and the bias increases with the number of instruments and orthogonality conditions. Moreover, Arellano and Bond (1991) show that the asymptotic approximation of the standard errors of their two-step GMM estimator is biased downwards, and they, as well as Judson and Owen (1999), find that the one-step estimator outperforms the two-step estimator.

Under the additional assumption of the quasi-stationarity of $y_{i,t}$, $\Delta y_{i,t-1}$ is uncorrelated with ε_{it}, and Blundell and Bond (1998) suggest a "system" GMM estimation where one stacks the model in the levels and in the first differences, imposes the cross-equation restriction that the coefficients entering in the two models be the same, and uses the full set of instruments (corresponding to the full set of orthogonality conditions for both models). Blundell and Bond report that in simulation the "system" GMM estimator is more efficient and stable than the Arellano–Bond procedure. This is the approach we adopt for the partial adjustment model.

3.3. Mismeasured prices

As we explain in more detail in Section 4, in this study the price of energy is measured with an error, because we do not know the exact price(s) faced by the household and impute the average price paid by residential customers in that area. The standard econometric theory shows that when a regressor is mismeasured, and the measurement error is classical, the estimated regression coefficient is downward biased (Greene, 2008, page 325–326). In our case, we must keep in mind that the mismeasured price enters in the construction of the dependent variable as well as in the right-hand side of the model as a regressor.

Alberini et al. (2010) discuss the implications of mismeasured prices, assuming for simplicity that only own price in entered in the right-hand side of Eq. (1). Specifically, if the measurement error is approximately constant within a dwelling over time, then it is eliminated by the LSDV procedure, and one obtains consistent estimates of the slopes. If the measurement error is classical (i.e., completely uncorrelated within and between the units in every period), then the price elasticity will be overstated (i.e., the absolute value of the estimated coefficient will be greater than $|\beta_1|$).[10]

How can one get around the mismeasurement problem? One approach is to restrict estimation to areas where mismeasurement is likely to be less severe (e.g., areas with only one utility). Another is to instrument for $\ln p^*$, which we do using state-level electricity and gas prices, or, in alternate runs, lagged electricity prices.

4. The sample and the data

4.1. The Data

In addition to data provided by individual utilities for their service territories (e.g., Borenstein, 2008, 2009) or otherwise geographically circumscribed areas (e.g., Shin, 1985; Garcia-Cerrutti, 2000; Bushnell and Mansur, 2005), earlier research has used the Department of Energy's Residential Energy Consumption Survey (RECS) to examine energy use patterns at the household level (e.g., Metcalf and Hassett, 1999; Reiss and White, 2005). Despite its national coverage, we were dissatisfied with this dataset, because it does not lend itself to panel data modeling (the length of the longitudinal component is at most

[9] We remind the reader that, when attention is restricted to those dwellings that appeared in more than one round of AHS survey, we have an unbalanced panel with T ranging from 2 to 6. A similar argument applies if we use dwelling-household effects instead of dwelling effects.

[10] Alberini et al. (2010) also examine whether it is possible to identify the price elasticity by exploiting the fact that the log real price, which appears in the right-hand side of Eq. (1), is the log of nominal price minus the log of the price index. They show that if only log nominal price and log price index are uncorrelated is it possible to obtain an unbiased estimate of the price elasticity. This is not the case here, since in this dataset log nominal price and log price index are positively correlated.

Table 2
Metropolitan areas selected for the study.

Metro area	Included?[a]	Metro area	Included?[a]
Atlanta–Sandy Springs–Marietta, GA	Yes	Minneapolis–St. Paul–Bloomington, MN–WI	Yes (Minneapolis–St Paul)
Austin–Round Rock, TX	Yes	Nashville–Davidson–Murfreesboro–Franklin, TN	Yes
Baltimore–Towson, MD	Yes	New Orleans–Metairie–Kenner, LA	Yes
Birmingham–Hoover, AL	Yes	New York–Northern New Jersey–Long Island, NY–NJ–PA	Yes (New York, Northern New Jersey)
Boston–Cambridge–Quincy, MA–NH	Yes	Oklahoma City, OK	Yes
Buffalo–Niagara Falls, NY	Yes	Orlando–Kissimmee, FL	Yes
Charlotte–Gastonia–Concord, NC–SC	Yes (Charlotte)	Philadelphia–Camden–Wilmington, PA–NJ–DE–MD	No
Chicago–Naperville–Joliet, IL–IN–WI	Yes (Chicago)	Phoenix–Mesa–Scottsdale, AZ	Yes
Cincinnati–Middletown, OH–KY–IN	No	Pittsburgh, PA	Yes
Cleveland–Elyria–Mentor, OH	Yes	Portland–Vancouver–Beaverton, OR–WA	Yes
Columbus, OH	Yes	Providence–New Bedford–Fall River, RI–MA	Yes (Providence)
Dallas–Fort Worth–Arlington, TX	Yes	Raleigh–Cary, NC	Yes
Denver–Aurora, CO \2	Yes	Richmond, VA	Yes
Detroit–Warren–Livonia, MI	Yes	Riverside–San Bernardino–Ontario, CA	Yes
Hartford–West Hartford–East Hartford, CT	Yes	Sacramento–Arden–Arcade–Roseville, CA	Yes
Houston–Sugar Land–Baytown, TX	Yes	St. Louis, MO–IL \3	No
Indianapolis–Carmel, IN	Yes	Salt Lake City, UT	Yes
Jacksonville, FL	Yes	San Antonio, TX	Yes
Kansas City, MO–KS	No	San Diego–Carlsbad–San Marcos, CA	Yes
Las Vegas–Paradise, NV	Yes	San Francisco–Oakland–Fremont, CA	Yes
Los Angeles–Long Beach–Santa Ana, CA	Yes	San Jose–Sunnyvale–Santa Clara, CA	Yes
Louisville/Jefferson County, KY–IN	Not present in the AHS	Seattle–Tacoma–Bellevue, WA	Yes
Memphis, TN–MS–AR	No	Tampa–St. Petersburg–Clearwater, FL	Yes
Miami–Fort Lauderdale–Pompano Beach, FL	Yes	Virginia Beach–Norfolk–Newport News, VA–NC	No
Milwaukee–Waukesha–West Allis, WI	Yes	Washington–Arlington–Alexandria, DC–VA–MD–WV	No

[a] Eligible because of unambiguous state identification in the AHS.

2), and the geographical identification is at too coarse a level to link each household with the relevant utilities (or to state-level or local policies or incentives).[11]

For these reasons, we assembled a large and comprehensive dataset that merged several sources of data. We use the American Housing Survey (AHS), a longitudinal study conducted by the Department of Housing and Urban Development where the cross-sectional units are dwellings (not households). The AHS contains extensive information about the structural characteristics of the dwelling, renovations and retrofits, home ownership and its financial aspects (mortgages, maintenance costs, etc.), appliances and heating/cooling systems, socio-demographic and economic circumstances of the occupants, and their assessment of the quality of the home and the neighborhood.

We focus on "national" survey AHS data for 1997, 1999, 2001, 2003, 2005, and 2007, which means that we can follow homes for up to $T=6$ periods. We augment this sample with observations from the AHS "metro"[12] surveys, which are conducted in even years in specific areas. We use the 2002, 2004 and 2007 metro surveys. Homes in the metro surveys are surveyed only once, so our sample is a mix of panel data plus multi-year cross-sections.

Because of privacy concerns, the AHS discloses the location of the dwelling only if the area has a population of 100,000 or more. We selected dwellings in the 54 cities corresponding to the 50 largest metropolitan areas in the U.S. as of 2008, unless the AHS SMSA identification makes it impossible to identify unambiguously which state the dwelling is located in. Table 2 lists the "candidate" metro areas (the 50 largest in the U.S. as of 2008) and indicates which are included in our study. These locations should ensure considerable variation in climate, age of the stock of housing and construction materials (which may affect efficiency of space heating and cooling), and utility prices.

Our sample is restricted to single-family homes and duplexes. We further restrict attention to homes that are owner-occupied or occupied by a tenant, and where these persons actually are responsible for paying the utility bills.[13] These criteria yielded a sample size of 120,333 observations. We deleted observations where i) the home was occupied as a residence for only part of the year, ii) the utility bills had been imputed using "hot deck" procedures, iii) the square footage (which should be an important determinant of energy usage) had been imputed using "hot deck" procedures, and/or iv) large and implausible changes in size were observed from one time period to the next.[14] This left us with 98,774 observations, which are further reduced to 98,772 when we further exclude residences where the heating equipment is shared with other units (2 observations).

Table 3 displays the distribution of this final sample by city. Table 4 summarizes information about the longitudinal component of our sample, examining the case where the cross-sectional units are the dwellings, and that where the cross-sectional units are dwelling-families. We have a total of 69,169 homes and 74,697 households (because families may move into and out of any given home during the study period).

4.2. Energy consumption and utilities' rates

The AHS reports the average monthly utility bill (and annual payments on heating oil fuel for those households that use heating oil) in the survey year, but does not report the electricity or gas tariffs, nor the actual energy consumption (in kilowatt-hours [kWh] or thousand cubic feet [MCF]).

[11] RECS provides the Census Region for each household. It provides the state identifier only if the household resides in one of the four most populous states (California, New York, Texas and Florida). HDD and CDD information is provided, but the true figures at the household's location are masked to ensure confidentiality.

[12] The Nationwide AHS sample returns to the same homes for every survey, and adds some newly constructed homes to keep the sample representative of the housing stock in the U.S. The metro surveys are conducted on a representative sample of homes in different cities every two years, but in the metro surveys different homes are selected in different waves for the same city.

[13] In other words, we exclude tenants where the utilities are included in the rent. Incentives to save on utilities may be different in this case.

[14] Specifically, we excluded observations with a change in the amount of energy or gas used that changed by more than 500% from one period to the next, while at the same time no renovation in the home and no square foot change was reported. Homes that experienced a change in square footage of more than 1000% from one period to the next, or with a change in square footage of more than 100% without a reported renovation to the home, were also discarded.

Table 3
Distribution of the sample by city. N = 98,772.

City	Nobs	Percent	City	Nobs	Percent
Anaheim	3618	3.66	Minneapolis	2112	2.14
Atlanta	3335	3.38	Monmouth	339	0.34
Austin	193	0.2	Nashville	275	0.28
Baltimore	1522	1.54	New Orleans	2387	2.42
Bergen-Passaic	428	0.43	New York	2585	2.62
Birmingham	343	0.35	Newark	612	0.62
Boston	1754	1.78	Northern New Jersey	659	0.67
Boulder	91	0.09	Oakland	793	0.8
Buffalo	1739	1.76	Oklahoma City	2752	2.79
Charlotte	2681	2.71	Orlando	434	0.44
Chicago	4306	4.36	Phoenix	3665	3.71
Cleveland	3137	3.18	Pittsburgh	3313	3.35
Columbus	3315	3.36	Providence	271	0.27
Dallas	3488	3.53	Raleigh-Durham	280	0.28
Denver	2415	2.45	Riverside San Bernardino	3883	3.93
Detroit	3467	3.51	Sacramento	2584	2.62
Ft. Worth	2992	3.03	Salt Lake	532	0.54
Hartford	2010	2.03	San Antonio	2781	2.82
Houston	2430	2.46	San Diego	2978	3.02
Indianapolis	2908	2.94	San Francisco	502	0.51
Jacksonville	357	0.36	San Jose	579	0.59
Jersey City	91	0.09	Santa Rosa	90	0.09
Las Vegas	453	0.46	Seattle	2706	2.74
Los Angeles	4870	4.93	Tacoma	224	0.23
Miami	4115	4.17	Tampa	2089	2.11
Middlesex County	300	0.3	Tucson	355	0.36
Milwaukee	2295	2.32	West Palm Beach	339	0.34

We must therefore construct consumption by taking the bills and dividing them by unit price. Unfortunately, the names of the utilities and the rate structure are not identified in the AHS either, so we were forced to impute average tariffs per kWh and cubic foot of gas for each dwelling in a number of ways.

For each metropolitan area, we identified the relevant gas and electric utilities using the listings provided by the state public utility commission, and a variety of on-line city services. We also consulted the list of counties covered by each utility, as documented in the Energy Information Agency (EIA) 861 forms database. We obtained utility-level price information from the EIA 861 forms (for electricity) and EIA 176 forms (for gas), which the utilities are required to file every year with the agency. Next, if the area was supplied by a single utility, we computed the average price per kWh (MCF) as the utility's annual revenue from sales to residential customers divided by the kWh (MCFs) sold to residential customers.[15]

If the area was supplied by more than one utility, we first computed the average price charged by each of them in the aforementioned fashion, and then constructed three alternative measures of price to use in our regressions. One, which we dub “residential price 1,” is a weighted average of each utility's average tariff per kWh, where the weights are proportional to the utility's customer base. The next, which we dub “residential price 2,” is also a weighted average, with weights assigned to represent the utility's dominance of the market.[16] The final constructed price (“residential price 3”) is a simple average of the individual utilities' average tariffs.[17] We followed a similar approach for gas utilities.

We use the prices of electricity and gas in two ways. First, we use them to create the dependent variables in our regressions: consumption of electricity and gas are obtained as the amount on the bill divided by (nominal) price. Second, (real) prices enter in the right-hand side of the demand equations.

[15] We note here that the EIA computes state-level electricity prices and gas prices exactly in this fashion—by taking the revenues of all utilities and dividing by all kWhs (or gas) served to residential households.

[16] If a utility dominates the market completely, despite the nominal existence of other utilities, that utility received a weight of ones and the others weights equal to zero. If two utilities were perceived to share the market in the area in a relatively equitable fashion, we assigned weights of 0.5 to each.

[17] Clearly, if there is a single utility, residential price 1, 2 and 3 are all identical.

Table 4
Distribution of the sample by length of the longitudinal component. N = 98,772.

	Unit: dwelling		Unit: dwelling-family	
T (length of the panel)	Freq.	Percent	Freq.	Percent
1	58,088	58.81	63,916	64.71
2	7094	7.18	9616	9.74
3	5315	5.38	6126	6.2
4	8232	8.33	6236	6.31
5	10,905	11.04	6740	6.82
6	9138	9.25	6138	6.21

We note here that, technically speaking, these average prices are not necessarily equal to the prices faced by the households. The majority of the utilities apply block pricing, but with such a geographically broad sample and such a long study period, it would be unfeasible to obtain the block pricing schemes used by each utility in each period. The only remaining econometric concern is that the price we use in our regression is measured with error. With our model and data construction, as explained in Section 3.3, this would make the household demand appear to be more elastic than it truly is.

We display descriptive statistics about prices and energy use in Table 5. Attention is restricted to the “price 1” variables because the others were very close to them.[18] Every home is served by electricity, and, as shown in Table 5, on average our households use about 930 kWh per month. This is in line with nationwide estimates collected by the Department of Energy using a dedicated survey (RECS). Just over three-quarters of the sample (76.6%) use natural gas as well, and almost 88% of such natural-gas connected households use gas heat. In a typical month, gas usage is 7.27 MCF.

Over the study period, the average price of electricity is about 11 cents per kWh (2007$). We found, however, evidence of considerable variation across states. The state with the lowest prices is Indiana (about 6.8 cents per kWh on average over the study period) and that with the highest prices is New York, where a kWh averaged almost 18 cents over the study period (2007$). The price of natural gas exhibits similar variability across locales. The average price per MCF is $11.41 (2007$), with Georgia exhibiting the lowest prices ($6.10, 2007$, on average) and Florida the highest ($17.83, 2007$).

Since we exploit the longitudinal feature of our data, it is important to check the extent of the variation in prices across and within units. In what follows, the units are the dwellings. We computed the total variation of real electricity prices and of log real electricity prices, and found that in each case the variation within dwellings accounted for only 4% of the total variation.[19] Gas prices are more variable over time: the “within” dwelling variation accounts for about 14% of total variation in real gas prices, and 15% of the total variation for log real gas prices.

4.3. Other key regressors

The weather is an important determinant of energy use. We computed heating and cooling degree-days (HDDs and CDDs) in the year prior to the date of the AHS survey using the T3 Global Summaries of the Day from NOAA's National Climatic Data Center. We matched each metro area with the T3 monitors in that area, computed

[18] The correlation coefficients between the “price 1” variables and the others were generally higher than 0.97.

[19] Our measure of variation is the sum of square deviations from the grand mean.

Table 5
Prices and monthly consumption of electricity and natural gas.

Variable label	Description	Obs	Mean	Std. dev.	Min	Max
kWh 1	Monthly electricity usage (kWh)	97,344	930.39	654.09	11.06	5697.54
gasuse1	Monthly gas usage (MCF)	67,154	7.27	5.50	0.23	71.86
residentialprice1_r	Price of electricity per kWh (2007 dollars)	98,487	0.11	0.03	0.05	0.22
gasprice1_r	Price of natural gas per MCF (2007 dollars)	94,315	11.42	3.10	3.90	22.89
Log kwh1		97,344	6.61	0.70	2.40	8.65
Log gasuse1		67,154	1.75	0.68	−1.49	4.27
Log residentialprice1_r		98,487	−2.23	0.26	−2.92	−1.49
Log gasprice1_r		94,315	2.40	0.26	1.36	3.13

the average of the mean temperatures for each day of the year prior to the date of the survey, created the HDD (CDD) for that day as 65 °F minus the average temperature (average temperature minus 65 °F), and summed over the year prior to the survey. This construction is the same as that used by the U.S. Department of Energy. The average HDDs and CDDs are 3450 and 1658 degree-days, respectively.

Our regressions control for dwelling characteristics, such as the age and size of the home, number of rooms, and number of floors, which come from the AHS. We enter all continuous variables in log form in the regression. Descriptive statistics for these variables are displayed in Table 6. The average size of the home is about 2000 square feet. This figure matches up nicely with the nationwide estimates for single-family homes and homes that are part of a two-unit building from the 1997, 2001, and 2005 RECS.

Despite removing observations with imputed square footage and implausible changes in square footage from one survey wave to the next, our sample does contain some observations with extremely small and extremely large values for size and the number of floors, so in our regressions we further restrict attention to homes no smaller than 400 square feet and no larger than 10,000. We also delete from the usable sample homes with more than 4 floors (single family homes are unlikely to have 5 or more floors).

Descriptive statistics for this cleaned sample are reported in the bottom panel of Table 6. The average square footage, house age and number of rooms are virtually unchanged. We note that a value of zero for the age of the house is correct: it means that the home was built in the same year of the survey. (The AHS does add new dwellings to mirror the stock of housing and new constructions. Homes with age 0 account for less than 1% of the sample.)

We report descriptive statistics about heating and cooling equipment, as well as appliances that use energy, in Table 7. All of this information comes from the AHS. Briefly, in terms of heating, about 67% of the sample has a gas heating system, 26% relies on electricity for heating, and about 5% on heating oil as the main source of heat. Homes with electric heat are located primarily in states with mild or warm climates, such as Arizona (66% of all Arizona homes), Florida (93.80%), Louisiana (43%), Tennessee (59%) and Texas (43.76%), or cheap electricity (e.g., Washington, 29%).

About 84% of the sample has some type of air conditioning, and about 67% has central air conditioning. Window units are used by 20% of the sample, sometimes alongside with central air conditioning. Only 2% of the observations have gas-powered heat pumps. Turning to appliances, virtually all homes have a fridge, almost 72% a dishwasher, 32% use gas-powered clothes dryers, and a little more than half of the sample has an electric stove.

Summary statistics of household characteristics are shown in Table 8. Briefly, we find that the average household income over the study period is about $88,000 (2007$). There are a small number of households (93, or 0.09%) that report negative income. When these persons are removed, the distribution of household income is essentially unchanged: The new sample average is still $88,000 (2007$).[20] The average household size is 2.8, 31% of the sample has small children, 22% has at least one person aged 65 or older living in this house, and almost 84% owns the home.

Table 6
House characteristics.

All observations					
Variable	Obs	Mean	Std. Dev.	Min	Max
Square footage	91,254	2073.96	1615.04	99	18,083
Basement (dummy)	98,772	0.37	0.48	0	1
Floors	98,772	1.83	0.96	1	21
Rooms	98,772	6.42	1.86	1	21
Age of the home	98,772	38.69	23.27	0	88
More than 400 sq ft and less than 10,000 sq ft, no more than 4 floors					
Square footage	88,732	1950.42	1141.95	400	9911
Basement (dummy)	88,732	0.35	0.48	0	1
Floors	88,732	1.77	0.83	1	4
Rooms	88,732	6.47	1.83	1	21
Age of the home	88,732	37.64	22.84	0	88

5. Results

5.1. Static models

Results for several specifications of the static model (see Eq. (1)) are reported in Table 9 for log electricity consumption, and in Table 10 for log gas consumption. The runs differ for the type of effects we include to account for unobserved heterogeneity.

We choose to report results for fixed city-, dwelling- and dwelling-family specific effects. We include city-specific effects because 1) the coefficients on most regressors are similar to those from a random effects model with dwelling-specific effects (estimated using GLS), 2) it stands to reason that homes and residents might share similar unobservable characteristics as other homes and residents in the same metro area, 3) we do not lose the observations with $T=1$, and 4) we are able to assess the impact on consumption of factors that vary widely across locales (e.g., home size, income, etc.) but little within a house over time. Finally, 5) assigning average prices at the metro-area level to each dwelling likely produces errors that are correlated within the metro area, biasing standard error estimates downward (Moulton, 1990). For this reason, we cluster the standard errors at the city level.

Fixed dwelling effects are a natural candidate, since the AHS follows a dwelling over time, while dwelling-family effects allow for unobservable heterogeneity to depend on the household as well as the home.[21] We prefer fixed effects because Hausman tests indicate that if the unobserved heterogeneity is modeled using random effects, these are correlated with the included regressors, which makes the GLS estimates inconsistent. For good measure, the standard errors are clustered at the city level (in specifications with city effects) or at the dwelling level (in specifications with dwelling and dwelling-household effects).

[20] In our regressions, which use log income, we will simply recode log income to zero when income is negative.

[21] The fixed effects also account for any selection of households into cities or homes.

Table 7
Heating and cooling equipment and appliances.

Variable	Obs	Mean	Std. dev.	Min	Max
Gas heat	98,772	0.67	0.47	0	1
Electric heat	98,772	0.26	0.44	0	1
Heating oil heat	98,772	0.05	0.23	0	1
Window A/C units	98,772	0.21	0.40	0	1
Number of rooms with A/C	20,251	1.78	1.02	1	8
Central A/C	98,772	0.67	0.47	0	1
Gas heat pump for A/C	98,772	0.03	0.16	0	1
Any type of A/C present	98,772	0.84	0.37	0	1
Refrigerator	98,772	0.9981	0.04	0	1
Dishwasher	98,772	0.72	0.45	0	1
Gas powered clothes dryer	98,772	0.32	0.47	0	1
Electric stove	98,772	0.53	0.50	0	1

Table 8
Household characteristics.

Variable	Obs	Mean	Std. dev.	Min	Max
Household income in thou. 2007$	98,772	87.92	115.49	−42.33	11,473.2
Number of household members	98,772	2.81	1.52	1	17
Young child (12 or less) lives in this housem (dummy)	98,772	0.31	0.46	0	1
Elderly person (65+) lives in this house	98,772	0.23	0.42	0	1
Owner (dummy)	98,772	0.84	0.37	0	1

Starting with Table 9, most of the coefficients are significant and have the expected sign. Importantly, column (A) – the results of a model with city-specific effects – shows that the elasticity of electricity use with respect to the price of electricity is −0.860, and the cross-elasticity with respect to the price of gas is positive and equal to 0.117, indicating that the two are substitutes.[22]

Consumption of electricity increases by 22% for every 10% increase in the square footage of the home, is 16% higher if the home has air conditioning, and about 15% higher if the home is heated using electricity. Dishwashers and electrical stoves increase usage by 8% and 7%, respectively (not displayed in the table). F tests reject the null hypotheses that heating/cooling systems are jointly equal to zero (F statistic = 37.65, p value less than 0.0001) and that the appliances are not associated with electricity consumption (F statistic = 38.05, p value less than 0.0001).

The income elasticity of electricity consumption is only about 0.02. One reason for such a low elasticity might be the fact that income is highly correlated with characteristics of the home, such as the size, the number of floors, and the presence of certain appliances. Once we removed these from the specification, income elasticity of electricity usage increased to almost 0.05.

Column (B) presents the results of a FE specification where the cross-sectional units are the homes. The own price elasticity is lower (−0.667), as expected, but the cross-price elasticity is slightly stronger. As expected, the coefficients on most other variables are much smaller than their counterparts in the city-specific effects specification, because these variables rarely change within a home over time. In column (C), we present the results of a model with dwelling-household specific effects. They are similar to those in column (B), with slightly stronger own- and cross-price elasticities.

As to the gas equation, columns (A)–(C) of Table 10 show that the own price elasticity ranges from −0.693 (city-specific effects) to −0.565 (dwelling-specific effects). The model with dwelling-household effects produces a price elasticity of −0.577. The cross-price elasticity is positive (0.150) and indicates that gas and electricity are substitutes in the model with city-specific effects (column (A)), but turns insignificant when we use dwelling-specific effects, and negative and insignificant in the model with dwelling-family effects.

The model with city-specific effects indicates that gas usage increases by 19% for every 10 percentage point increase in the square footage of the home, and is about 24% larger in homes with gas heating systems. The impact of these variables is small and statistically insignificant in the variants with dwelling- and dwelling-household effects.

5.2. Robustness checks

Our first order of business is to examine the size of the potential bias due to measurement errors in the prices of electricity and gas. To see if such a bias is severe, we began with regressions where the sample is restricted to metro areas served by one utility. We argue that the measurement error due to our price imputation procedure is smaller in single-utility areas. For electricity usage, the results of these runs are reported in columns (D) and (E) of Table 9 for the models with dwelling-specific effects and dwelling-family effects. Similar models for gas usage are displayed in columns (D) and (E) of Table 10. Clearly, the own-price elasticities are very close (and slightly higher than) to their counterparts in columns (B) and (C).

Next, we estimated a log kWh model with fixed dwelling-specific effects, the regressors as in Table 9, and log electricity price (but no gas price). If we do not instrument for electricity price, the own price elasticity is −0.6794. When we instrument for log electricity price using the log of the state average prices of electricity and gas as the identifying instruments, the coefficient on log price is −.67907.[23] Using log state-level electricity price as the only identifying instrument produces an own price elasticity of electricity demand of −0.6584, while replacing that with the first lag of log price of electricity in the metro area yields an elasticity of −0.6108.

Finally, we estimated a model where the dependent variable is the log electricity bill, the right-hand side includes fixed dwelling-specific effects, all other controls, the log of nominal electricity price and the log of the CPI (but no gas price).[24] The coefficient on log nominal electricity price is 0.3223 and that on log CPI is 0.5981. The corresponding estimates of the elasticity with respect to the price of electricity are −0.6777 and −0.5891 (from the coefficient on log price and log CPI, respectively). Although we argue in Section 3.3 that these are both likely to overstate the true elasticity, they are within 10–15% of the original estimates and of the IV estimates of the price elasticity, suggesting that the impact of measurement error is modest.

Observers sometimes speculate that high price elasticities might be capturing the effect of conservation and energy efficiency installations made possible by the utilities' DSM initiatives.[25] We do have the DSM expenditure per customer by the electrical utilities that serve any given metro area, and, indeed, it is indeed positively correlated with electricity price (correlation coefficient 0.28). However, when we add DSM expenditure per customer (in real terms) in the right-hand side of the log kWh model, the coefficient on log electricity price is virtually unchanged (−0.657).

To check if consumption depends on current or recent prices, we also estimated models similar to the ones shown in Tables 9 and 10, but where we further included lagged prices. We found that i) the

[22] It is useful to compare these figures with their counterparts in an OLS regression that ignores unobserved heterogeneity. The own price elasticity when the city effects are suppressed is −1. Adding state effects (but no city effects) makes it −0.894.

[23] Our instruments are in the spirit of Black and Kniesner (2003), who propose using another mismeasured variable (i.e., state-level annual average prices) to clean out the measurement error in the original mismeasured regressor (here, average price in the metro area).

[24] This model is obtained on recognizing that i) log kWh is equal to log bill minus log nominal price, and ii) in the right-hand side of the demand equation, log real price is equal to log nominal price minus log CPI.

[25] We are grateful to Mark Jacobsen, personal communication, 2010, for raising this issue.

Table 9
Static model: selected regression results. Dependent variable: log of electricity usage (lkWh1).

	(A)	(B)	(C)	(D) only one utility	(E) only one utility	(F) electric heat	(G) gas heat
log elec price	−0.860***	−0.667***	−0.681***	−0.685***	−0.692***	−0.679**	−0.825***
	(−9.37)	(−9.69)	(−8.16)	(−8.26)	(−6.82)	(−3.22)	(−8.12)
log gas price	0.117*	0.122*	0.139*	0.115*	0.107	0.126*	0.102
	(2.02)	(2.45)	(2.36)	(1.97)	(1.58)	(2.04)	(1.63)
log sq. ft.	0.216***	0.0593	0.0522	0.0538	0.0396	0.226***	0.220***
	(11.05)	(1.64)	(1.21)	(1.29)	(0.81)	(7.12)	(9.15)
Age of the home	0.00553***	−0.00477	−0.00195	−0.00164	−0.000416	0.00685***	0.00517***
	(8.38)	(−1.70)	(−0.53)	(−0.48)	(−0.09)	(7.44)	(7.39)
Age of the home squared	−5.4E−5***	4.91E−05	3.07E−05	1.54E−05	4.86E−06	−6.32E−05***	−4.98E−05***
	(−7.56)	(1.69)	(0.81)	(0.43)	(0.10)	(−5.19)	(−6.80)
Owns the home	0.0696***	−0.0558	0.0408	−0.0803	0.0215	0.0899**	0.0518**
	(4.86)	(−1.69)	(0.70)	(−1.79)	(0.26)	(3.33)	(3.25)
No. of rooms	0.0659***	0.0159***	0.0103	0.0202***	0.0130	0.0701***	0.0626***
	(14.74)	(3.42)	(1.94)	(3.39)	(1.91)	(8.14)	(14.07)
No. of floors	−0.0171*	0.0371	0.0297	0.0425	0.0297	−0.0524**	0.00476
	(−2.07)	(1.34)	(0.85)	(1.29)	(0.71)	(−3.35)	(0.59)
log Hhold income	0.0225***	0.00906*	0.00677	0.0107*	0.00804	0.0251***	0.0208***
	(8.83)	(2.30)	(1.49)	(2.12)	(1.38)	(6.10)	(8.08)
Young child dummy	0.0963***	0.0721***	0.0353	0.0614**	0.0335	0.0913***	0.0964***
	(15.06)	(4.24)	(1.48)	(2.82)	(1.09)	(11.36)	(11.93)
Elderly dummy	−0.0390***	−0.0204	−0.00932	−0.0137	−0.00911	−0.0154	−0.0400***
	(−4.20)	(−0.88)	(−0.32)	(−0.49)	(−0.25)	(−0.95)	(−4.22)
Log CDD	0.0727***	0.0299	0.0250	0.0417	0.0272	0.141**	0.0762**
	(3.58)	(1.07)	(0.78)	(1.20)	(0.68)	(3.14)	(3.33)
Log HDD	0.00350	−0.0123	0.00277	−0.0278	−0.0244	0.0393	0.0384
	(0.07)	(−0.39)	(0.07)	(−0.58)	(−0.42)	(0.63)	(0.54)
Gas heat dummy	−0.0990**	−0.0152	−0.0183	−0.00105	−0.0704		
	(−2.79)	(−0.17)	(−0.18)	(−0.01)	(−0.56)		
Electric heat dummy	0.154***	0.106	0.123	0.117	0.0722		
	(4.72)	(1.23)	(1.20)	(1.09)	(0.57)		
Heating oil heat dummy	−0.0971*	0.00475	0.103	0.0230	0.0945		
	(−2.28)	(0.04)	(0.64)	(0.15)	(0.51)		
A/C	0.161***	0.0572*	0.0493	0.0566	0.0445	0.0928*	0.176***
	(8.00)	(2.21)	(1.61)	(1.71)	(1.15)	(2.63)	(8.61)
Constant	1.422**	4.053***	3.861***	4.000***	4.212***	1.510*	1.094
	(2.72)	(7.61)	(6.07)	(5.64)	(4.97)	(2.12)	(1.49)
Effects	City	Dwelling	Dwelling-family	Dwelling	Dwelling-family	City	City
R-squared	0.457	0.0557	0.0491	0.0564	0.0481	0.418	0.407
N. of cases	82,905	82,905	82,905	48,027	48,027	22,003	55,688
Std. errs. clustered	City	Dwelling	Dwelling	Dwelling	Dwelling	City	City

* $p<0.05$, ** $p<0.01$, *** $p<0.001$.
t statistics, not standard errors, are reported in parentheses.

coefficients on contemporaneous price were strongly significant and similar to their counterparts in Tables 9 and 10, and ii) the coefficients on lagged prices were very small in magnitude and insignificant at the conventional levels. This is unsurprising if we recall that the "previous period" is usually two years prior to the current observations. We would expect people to react to changes in recent billing periods, and billing periods are usually one month (see Reiss and White, 2008).

To make that our results are not driven by outliers, we experimented with trimming the sample, e.g., we excluded the observations in the bottom and top 1%, 2.5%, etc. of the distribution of kWh s and MCFs. The elasticities and most other coefficients remained virtually the same as those in Tables 9 and 10.

In columns (F) and (G) of Tables 9 and 10, we report regression results for the subsamples with electric heat and gas heat. We report only the results for the models with city-specific effects for the sake of brevity, but the same qualitative results hold for the models with dwelling- and dwelling-households effects (although the magnitude of the coefficients is slightly smaller). In contrast to earlier literature (Metcalf and Hassett, 1999; Reiss and White, 2005), we find households with electric heating systems are actually *less* responsive to the price of electricity than households that use gas heat. Households with gas heat are slightly *more* sensitive to the price of gas than households that use electric heat.

However, Wald tests of the null that the elasticities are the same across the two groups fail to reject the null. For example, if attention is restricted to the equations in columns (F) and (G) of Table 9, the Wald statistic of the null of identical own price elasticities is only 1.13 (p-value 0.29).

The Wald statistics are even smaller in runs with fixed dwelling (or dwelling-household) effects. One possible explanation for this is that the sample size is rather uneven across the groups of homes served with electric and gas heat. The number of observations with electric heat is 23,542, but drops to 8416 when only true "panels" are used. This is only about 8% of the total sample. The resulting increase in variance may help explain the lack of significant differences across the two subsamples.

Finally, we estimated models where we allow the responsiveness to energy prices to vary with the quartile of the income distribution that the household falls in. We find that the responsiveness to prices is a bit higher in the first quartile, and declines monotonically by quartile. For example, the elasticity of electricity consumption with respect to electricity price is −0.681 among households in the first income quartile, −0.673 among those in the second quartile, −0.663 among those in the third, and −0.645 among those in the fourth. An F test of the null that these elasticities are all identical rejects the null at the 1% level or better (F statistic = 15.96, p-value less than 0.0001).

5.3. Dynamic Models and Models with Investments

Turning to the partial adjustment model, we report results based on the Blundell-Bond estimation procedure in Table 11. Column (A)

Table 10
Static model: selected regression results. Dependent variable: log of gas usage (lgasuse1).

	(A)	(B)	(C)	(D) only one utility	(E) only one utility	(F) electric heat	(G) gas heat
log elec price	0.150*	0.0376	−0.0334	0.0763	0.0192	0.461	0.128*
	(2.15)	(0.48)	(−0.36)	(0.78)	(0.16)	(1.49)	(2.12)
log gas price	−0.693***	−0.565***	−0.577***	−0.583***	−0.587***	−0.634***	−0.693***
	(−6.57)	(−9.51)	(−8.21)	(−8.31)	(−7.24)	(−4.52)	(−6.45)
log sq. ft.	0.189***	0.0524	0.0459	0.0490	0.0439	0.120*	0.201***
	(9.88)	(1.26)	(0.89)	(1.03)	(0.76)	(2.33)	(10.25)
Age of the home	0.00383***	0.0000321	0.000597	−0.0000686	−0.000542	0.00252	0.00384***
	(5.87)	(0.01)	(0.15)	(−0.02)	(−0.12)	(1.06)	(5.85)
Age of the home squared	−9.11 E−06	6.84E−06	1.68E−05	6.19E−06	2.01E−05	−1.07E−05	−7.25E−06
	(−1.30)	(0.22)	(0.42)	(0.16)	(0.42)	(−0.47)	(−1.05)
Owns the Home	0.0322*	−0.0426	−0.00991	−0.0331	−0.00764	0.00436	0.0412**
	(2.56)	(−1.08)	(−0.14)	(−0.61)	(−0.07)	(0.15)	(3.28)
No. of Rooms	0.0549***	0.0149**	0.0125	0.0171*	0.0140	0.0695***	0.0536***
	(18.61)	(2.72)	(1.93)	(2.51)	(1.74)	(7.37)	(17.83)
No. of Floors	0.00974	0.0573	0.0485	0.0645	0.0673	−0.0224	0.00998
	(1.18)	(1.75)	(1.09)	(1.72)	(1.32)	(−0.62)	(1.30)
log Hhold Income	0.00357	0.00285	0.00298	0.00446	0.00313	−0.00950	0.00497*
	(1.61)	(0.60)	(0.55)	(0.74)	(0.47)	(−1.40)	(2.20)
Young child dummy	0.0711***	0.0635**	0.0657*	0.0658*	0.0813*	0.0549***	0.0683***
	(12.01)	(3.05)	(2.25)	(2.44)	(2.18)	(3.73)	(11.12)
Elderly dummy	0.0640***	−0.00246	0.00278	−0.00266	−0.000376	0.0574*	0.0659***
	(7.23)	(−0.10)	(0.08)	(−0.08)	(−0.01)	(2.53)	(7.40)
Log CDD	−0.00384	−0.0262	−0.00987	−0.0189	0.000143	0.105	0.00162
	(−0.13)	(−0.85)	(−0.28)	(−0.49)	(0.00)	(1.24)	(0.06)
Log HDD	0.0991	0.105*	0.114	0.192*	0.198*	−0.0936	0.149**
	(1.67)	(1.99)	(1.93)	(2.20)	(2.15)	(−1.15)	(2.83)
Gas heat dummy	0.215***	−0.0797	−0.0890	−0.0855	−0.108		
	(4.20)	(−0.55)	(−0.48)	(−0.36)	(−0.45)		
Electric heat dummy	0.0211	−0.225	−0.226	−0.237	−0.229		
	(0.47)	(−1.47)	(−1.15)	(−0.95)	(−0.90)		
Heating oil heat dummy	−0.938***	−0.730**	−0.564*	−0.677	−0.506		
	(−11.47)	(−2.82)	(−1.99)	(−1.91)	(−1.36)		
A/C	−0.0147	0.0171	0.00614	−0.000232	−0.0155	−0.0348	−0.0154
	(−0.94)	(0.62)	(0.18)	(−0.01)	(−0.36)	(−1.09)	(−1.01)
Constant	0.214	1.931**	1.587*	1.334	1.050	3.746**	0.206
	(0.35)	(2.76)	(1.97)	(1.29)	(0.95)	(2.79)	(0.33)
Effects	City	Dwelling	Dwelling-family	Dwelling	Dwelling-family	City	City
R-squared	0.438	0.0497	0.0465	0.0556	0.0512	0.250	0.429
N. of cases	59,492	59,492	59,492	34,371	34,371	5,176	53,027
Std. err clustering	City	Dwelling	Dwelling	Dwelling	Dwelling	City	City

* $p<0.05$, ** $p<0.01$, *** $p<0.001$.
t statistics, not standard errors, are reported in parentheses.

shows that the short-run own price elasticity of electricity consumption is −0.736, and the long-run one is −0.814, while the short-run cross-price elasticity (with respect to gas) is 0.265, and the long-run one is 0.293. For gas consumption, shown in column (C), the short-run own price elasticity is −0.572 and the long-run one is −0.647. The price of electricity is not significant in the gas equations. These equations include controls for the heating and cooling system, and we interpret them to imply adjustment when the current heating and cooling technology is considered irreversible.

In specifications (B) and (D) for electricity and gas, respectively, we exclude heating, cooling, and appliance dummies from the regression and interpret the result to apply when the choice of heating and cooling technology is reversible. It has been argued that durable goods and heating and cooling equipment are variable in the long-run, hence these specifications should result in a more pronounced response to energy prices. In fact, we do find slightly elevated price elasticities, but the differences are minor, on the order of 2% for electricity regressions, and 6% for gas regressions.

6. Discussion and Conclusions

The price and income elasticities of residential energy demand are important inputs into assessments of the effects of energy policies, demand forecasts, and greenhouse gas (GHG) emissions and impacts models. Existing estimates based on household-level energy consumption are based on either old data, or on recent, abrupt changes in prices due to supply conditions in geographically limited areas, and so it is unclear whether they are appropriate nationwide.

To address these external validity limitations, we assembled a mixed panel/multi-year cross-sectional dataset of households in the 50 largest metropolitan areas in the United States as of 2008. Our dataset documents utility bills, heating and cooling systems, appliances, and dwelling and household characteristics for over 69,000 dwellings (over 74,000 households) in the American Housing Survey from 1997 to 2007, for a total of over 98,000 observations. We merged these data with utility prices, and heating and cooling degree-days at the metro area level. To our knowledge, this is the most comprehensive set of data for examining household residential energy usage at the national level, containing the broadest geographical coverage, and with the longest longitudinal component (max $T=6$).

We estimate demand functions for electricity and gas. We control for unobserved heterogeneity in three alternate ways: (i) city-specific fixed effects exploit the variation in prices, dwelling characteristics, and state and local policies between observations, while (ii) dwelling-specific and (iii) dwelling-household effects rely on variation of prices, weather, and other local characteristics over time.

We find strong household response to energy prices, both in the short and long term. From the static models, we get estimates of the own price elasticity of electricity demand in the −0.860 to −0.667 range, while the own price elasticity of gas demand is −0.693 to −0.566. The dynamic models produce similar estimates, with short-

Table 11
Blundell–Bond estimates. Dynamic models. (Model based on dwelling-specific effects.)

	Log of energy usage — lkWh		log of energy usage — lMCF	
	(A) dwelling effect	(B) no HVAC	(C) dwelling effect	(D) no HVAC
Lag consumption	0.0958***	0.0939***	0.116***	0.123***
	(6.09)	(5.83)	(6.20)	(6.41)
Log electric price	−0.736***	−0.743***	−0.0716	−0.0821
	(−12.26)	(−12.29)	(−0.91)	(−1.05)
Log gas price	0.265***	0.283***	−0.572***	−0.586***
	(5.15)	(5.56)	(−9.15)	(−9.32)
Log sq. ft	0.142**	0.142**	0.140	0.137
	(2.64)	(2.65)	(1.91)	(1.83)
Age of the home	−0.00624*	−0.00699*	0.00691*	0.00720*
	(−2.04)	(−2.22)	(2.22)	(2.31)
Age of the home squared	0.0000497	0.0000522	−0.0000353	−0.0000365
	(1.63)	(1.68)	(−1.07)	(−1.11)
Owns the home	−0.0261	−0.0310	−0.0168	−0.0101
	(−0.90)	(−1.06)	(−0.45)	(−0.27)
No. rooms	0.0128***	0.0126***	0.0162***	0.0162***
	(3.70)	(3.60)	(3.72)	(3.70)
No. floors	0.00976	−0.00316	0.149***	0.164***
	(0.45)	(−0.14)	(4.98)	(5.40)
Log Hhold income	0.00935**	0.00925**	0.00318	0.00425
	(3.09)	(3.05)	(0.93)	(1.23)
Young child dummy	0.0725***	0.0714***	0.0574**	0.0578**
	(4.89)	(4.80)	(3.01)	(2.99)
Elderly dummy	−0.00728	−0.00829	0.0160	0.0190
	(−0.36)	(−0.41)	(0.69)	(0.81)
log CDD	0.0660**	0.0793***	−0.0297	−0.0304
	(3.01)	(3.56)	(−1.21)	(−1.22)
log HDD	0.0222	0.00478	0.200***	0.202***
	(0.95)	(0.21)	(5.46)	(5.41)
Constant	2.389***	2.422***	−0.661	−0.844
	(4.06)	(4.08)	(−0.91)	(−1.14)
N. of cases	24,487	24,487	17,679	17,679
Long term elasticity	−0.8140	−0.8200	−0.6471	−0.6682

* p<0.05, ** p<0.01, *** p<0.001.
t statistics, not standard errors, are reported in parentheses.

run (long-run) own-price elasticity of demand of −0.736 (−0.814) for electricity and −0.572 (−0.647) for gas.

Our relatively high price elasticity of demand is in sharp contrast with much of the literature on residential energy consumption in the United States, and with the figures used in current government agency practice. In its Annual Energy Outlook, for example, the Energy Information Agency (EIA) historically employed a short-term price elasticity of −0.15 for non-electric energy. In their 2010 report, EIA adopts an electric elasticity of −0.30 in anticipation of improved consumer awareness resulting from recent smart grid projects.[26]

By contrast, our estimate of the income elasticity is low, and only when we remove dwelling characteristics from the right-hand side of the regression equations does it reach 0.05. This figure is consistent with its counterparts in Rehdanz (2007) and Meier and Rehdanz (2010), who examine residential space heating *expenditures* in Germany and the U.K., respectively, using household-level data, but much lower than the income elasticity of energy demand (from all sources and sectors) typically used in many integrated assessment models (see Webster et al., 2008).

Taken together, our findings suggest that when prices increase households tend to substitute other inputs for energy and choose less energy-intensive appliances (or homes), and that as incomes rise, households tend to exhibit preferences for less energy-intensive appliances and homes (Webster et al., 2008). We leave it to future research to explore *which* energy efficiency investments, changes the stock of appliances, or conservation practices people undertake in response to price changes.

[26] The text refers specifically to smart grid projects funded under the American Recovery and Reinvestment Act of 2009 http://www.eia.doe.gov/oiaf/aeo/assumption/residential.html and EIA (2010).

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