Energy Policy 97 (2016) 235–249

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

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

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HIGHLIGHTS

- The price elasticity of residential electricity demand varies widely across studies.
- We use three large datasets from the US to examine reasons for such wide variation.
- Some assessed effects include aggregation, unobserved heterogeneity, and price trends.
- Correcting for such issues can change the estimated price elasticity by 50–100%.

ARTICLE INFO

Article history:
Received 26 November 2015
Received in revised form
29 June 2016
Accepted 19 July 2016
Available online 28 July 2016

JEL classification:
Q41
D12

Keywords:
Residential electricity demand
Price elasticity of demand
Household-level data
Rebound effect
Energy demand forecast

ABSTRACT

Price elasticity estimates of residential electricity demand vary widely across the energy economics and policy literature. In this paper, we seek to explain these findings using three nationwide datasets from the U.S. – the American Housing Survey, Forms EIA-861, and the Residential Energy Consumption Survey. 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 average price. Whether prices are rising or falling appears to have little effect on our estimates. We also find that aggregating our data can result in both higher and lower price elasticity estimates, depending on the dataset used, and that controlling for unit-level fixed effects with panel data generally results in more inelastic demand functions. 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.

1. Introduction

In energy economics and policy, it is important to understand how the demand for an energy input—such as electricity or natural gas—changes when the price of that input changes. This information, which often conveniently summarized into a price elasticity, namely the percentage change in demand when the price changes by 1%, allows regulators to estimate the welfare effects experienced by consumers as the regulatory environment is changed, as utilities enter or exit a market, and adequately plan infrastructure and grid investments (Labandeira et al., 2012).

The price elasticity of demand is also a key determinant of the tax revenue, effectiveness, and the burden falling on the shoulders of electricity generators, industry and consumers in the presence of a carbon tax, the remedy that has been put in place in some countries (e.g. Australia, the UK, and Sweden[1]) to encourage a shift away from fossil fuel usage and the associated CO_2 emissions (e.g., Hammar and Sjöström, 2011; Mori, 2012).

Given much recent interest and policy focus on improving 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

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[1] For full list of countries, see http://www.carbontax.org/ (last accessed 31.08.15). In the case of the UK, a climate levy imposes a tax on fossil fuels, but not as a direct function of its carbon content.

http://dx.doi.org/10.1016/j.enpol.2016.07.031

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]

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 type of data used (panels, pseudo-panels, cross-sections, time series), 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 (Blázquez 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. From the output of the National Energy Modeling Systems model, the Energy Information Agency estimates 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 (U.S. Energy Information Administration, 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.[4]

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.

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.

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 (kW h) 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, 2014; Ito, 2014; Allcott, 2011; 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]

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 about total sales (in kW h) for each class of customers, including residential consumers.

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. 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. This finding is similar to that of Halvorsen and Larsen's (2013), who show that the effect of aggregation depends crucially on the distribution of price and household income in the sample. With the Forms EIA-861 data, more aggregation produces a more elastic

[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] Price elasticities of commercial and industrial demand are in relatively scarce supply. Mori (2012) surveys the literature and reports a handful of studies, with long run price elasticities ranging between −0.32 and −1.37 for commercial demand, and −0.22 and −0.83 for industrial demand. Lim et al. (2014) use 41 years' worth of data from Korea and produce estimates of −0.42 (short run) and −1.01 (long run) for the service sector, For Japan, Hosoe and Akiyama (2009) estimate commercial and industrial elasticities between −0.09 and −0.30 (short run) and −0.12 and −0.56 (long run), with more elastic demand in rural areas. Kamerschen and Porter (2004) report commercial and industrial elasticities of −0.34 to −0.55.

[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.