Quantifying Inattention to Local Energy Prices: A Novel Approach and New Evidence for Nine Appliance Markets

Sébastien Houde,* Erica Myers†

This study proposes a novel approach to quantify consumers' response to local energy prices when purchasing energy intensive durables. This estimate is a critical input for the design of successful policy instruments for reducing the amount of carbon emissions and other pollution generated from energy production. An increasing proportion of U.S. carbon dioxide emissions, around 40%, come from the residential and commercial buildings sector. Thus, policies designed to effectively reduce the energy used in buildings through more efficient appliances and tighter building shells will have a major impact on the nation's greenhouse gas emissions.

Work on the relationship between energy prices and appliance choice has found mixed results. The bulk of the evidence comes from early work that found that consumers substantially discount future energy costs (e.g. Hausman, 1979; Dubin and McFadden, 1984). More recently, Rapson (2014) developed a structural model of demand for air-conditioners and found that consumers value the stream of future savings from high efficiency units. Houde (2014) found that consumers are highly heterogeneous in their response to local energy prices when purchasing refrigerators. Some consumers appear to rely on a local measure of energy prices, especially among higher income households, but a fair share of consumers appear to simply dismiss energy information altogether. All these studies have relied primarily on cross-sectional variation in energy prices and variants of a discrete choice model. In the US, cross-sectional variation in energy prices is rich, but may be correlated with time-invariant differences across regions, stemming from demographic variation and other variation in consumer preferences. Jacobsen (2015) is one example of a recent study that attempts to address this issue by using state level panel data to assess the effect of energy prices on Energy Star market shares. He finds very little evidence that energy prices affect the market share of Energy Star appliances. An important caveat of this study is that consumers may value Energy Star models for reasons other than energy savings, as shown by Newell and Sikimakii (2014). Energy Star is, therefore, an imperfect proxy for energy efficiency. Finally, Lucas and Metcalf (2014) use a stated preferences survey to show that it is unlikely that consumers respond to local energy prices when purchasing appliances given that the mandatory energy label relies on a national average.

In sum, as of today this literature remains largely inconclusive chiefly because studies have had important differences in modeling assumptions, preferences elicitation method (revealed vs. stated), source of variation in energy prices, and dependent variables. Moreover, most studies only consider one type of appliance in their empirical investigation, which makes it hard to assess the external validity of a specific approach.

*Department of Agricultural and Resource Economics, University of Maryland, shoude@umd.edu.
†Department of Agricultural and Consumer Economics, University of Illinois, ecmyers@illinois.edu.

The contribution of our study is to address these shortcomings by providing a framework that (1) allows to easily exploit different source of variation in local energy prices; (2) requires minimal modeling of the choice process, but has a clear link with utility and profit maximization, and (3) is easily scalable. We expect that our study will provide highly credible estimates of consumers' response to local energy prices for nine appliance categories.

This study will build on previous work by using several levels of price variation that are unique to the literature on the effect of energy prices on appliance choice. Moreover, our outcome variable, annual kwh of energy used by appliances, is an important input to the design of policies targeting long-term energy demand. First, using a unique administrative dataset with micro-level sales data from a large appliance retailer, we will exploit county-level variation in energy prices over time to estimate the effect of price movements on demand for appliance energy efficiency. Our measure of energy efficiency is the energy consumption of a given appliance model as reported by manufacturers. Absent a large rebound effect, this outcome variable is a very accurate proxy of long-term energy demand associated with a given appliance category. County fixed-effects will allow us to control for time-invariant differences in demographics and consumer preferences across counties within the same state. In addition, in other estimations, we will build a household panel with repeated purchases, which will allow us to control for household fixed effects and exploit movements of households to different geographic areas over time. Household fixed effects account for the time-invariant preferences of households, allowing us to control for compositional changes in populations that may drive differences in preferences for appliances.

Lastly, we will exploit variation in energy price for households located on either side of the geographic boundaries of utilities. We will construct county-border fixed effects that will take the value of one for a county and every county that borders that county. This will allow us to identify the effect of having a higher electricity price in one county relative to surrounding counties on appliance purchase choices. The identification in this method is coming from utility borders where prices may differ for neighboring counties, but weather, socio-economic characteristics, and other factors that affect appliance purchase choices are more likely to be similar.

With all of the approaches described above, county level electricity prices may suffer from both endogeneity with time-varying preferences for appliance efficiency and measurement error. In order to address these issues, we will construct an instrument for county-level electricity price using variation in local utilities' fuel mixes and fuel price movements over time. Following Mansur and Kahn (2013), we construct price instruments using the product of the local utility's capacity shares of coal, oil and gas-fired power plants with their respective annual average fuel price. The assumption of this approach is that the variation in average fuel costs for utilities over time should only effect consumers' appliance choices through their effects on retail prices.

Another key contribution of this study is to link reduced-form estimates of the effect of local energy prices on long-term energy demand to a framework with utility maximizing

consumers and profit maximizing firms. This allows us to quantify the share of inattentive consumers in a given market. We present this framework next.

Framework

Our framework borrows from Ito and Sallee (2015) and Allcott et al. (2014). We consider a market with two types of consumers that have preferences over two dimensions of an energy intensive durable: energy consumption (e) and quality (a). For simplicity, we assume a continuum of products on the market. Therefore, a consumer's choice of an energy intensive durable is a bundle (e, a). In addition consumers pay the prices p_e and p_a for e and a, respectively, consumers also pay a price f for operating the product once the product is purchased from the firm. As in Allcott et al. (2014), consumers differ in their ability to forecast/compute the price f. A share θ of consumers are inattentive to operating costs (type I). This is as if they were discounting f by the factor δ, where $0 < \delta < 1$. Other consumers are fully attentive to f (type A). Finally, we assume quasi-linear preferences–the numeraire good is x and income is y. The problem of consumer I is:

$$\max_{e,a} U(e,a) \quad \text{s.t. } x + p_e e + p_a a + \delta f e \leq y \tag{1}$$

For consumer A, we have the same problem except that $\delta = 1$. Solving the maximization problem of consumers I and A, we have four demand equations: e_I^*, e_A^*, a_I^*, and a_A^*. The aggregate demand for e, noted $\bar{e}$, is thus: $\bar{e} = \theta e_I^* + (1-\theta) e_A^*$.

On the supply-side, we assume a perfectly competitive market for the manufacturing of e and a.[1] At the competitive equilibrium, prices equal marginal costs: $p_e = c_e$ and $p_a = c_a$. The above assumptions imply that for attentive consumers, a change in the cost of operating the durable should have the same impact that a change in the marginal cost of reducing e, i.e.,: $\frac{\partial e_A^*}{\partial f} = \frac{\partial e_A^*}{\partial p_e} = \frac{\partial e_A^*}{\partial c_e}$. But, for inattentive consumers, we have: $\frac{\partial e_I^*}{\partial f} < \frac{\partial e_I^*}{\partial p_e} = \frac{\partial e_I^*}{\partial c_e} = \frac{\partial e_A^*}{\partial c_e} = \frac{\partial \bar{e}}{\partial c_e}$.

Our test of inattention thus consists of investigating whether $\frac{\partial \bar{e}_I}{\partial f}$ is smaller than $\frac{\partial \bar{e}_I}{\partial c_e}$. Assuming that consumers of type I are fully inattentive,[2] i.e., $\delta = 0$, we can quantity the share of inattentive consumers in a given market (θ):

$$\theta = 1 - \frac{\frac{\partial \bar{e}}{\partial f}}{\frac{\partial \bar{e}}{\partial c_e}}. \tag{2}$$

From Theory to Empirics

Our first quantity of interest is $\frac{\partial \bar{e}}{\partial f}$, which we will estimate directly using variation in local energy prices and information about the attribute e chosen by consumers in markets subject to different energy prices as discussed previously.

[1] Manufacturers do not produce e, but the inverse of e, which can be thought as energy efficiency.

[2] Sallee (2015) and Houde (2014) provide the micro-foundations of a framework where consumers are either fully inattentive or fully attentive to energy operating costs.

For the quantity $\frac{\partial \bar{e}}{\partial c_e}$, first note that the marginal cost c_e does not vary over regions and variations over time would be hard to distinguish from demand shocks impacting $\bar{e}$. Instead of directly attempting to estimate $\frac{\partial \bar{e}}{\partial c_e}$, we decompose it as follows. Define $T_j(e,a)$ as the price of product j, which in our case is a bundle (e^*, a^*) chosen by consumer of type $j = \{A, I\}$. In practice, $T_j(e,a)$ is simply the retail price of product j. By the chain rule, we have $\frac{\partial \bar{e}}{\partial c_e} = \frac{\partial \bar{e}}{\partial T_j(e,a)} \cdot \frac{\partial T_j(e,a)}{\partial c_e}$. The term $\frac{\partial \bar{e}}{\partial T_j(e,a)}$ is simply the change in the aggregate demand for e for a change in the price of product j. This can be easily estimated using a simple demand model that captures own- and cross-price elasticities. The term $\frac{\partial T_j(e,a)}{\partial c_e}$ is the pass-through of the marginal cost to the product price. To illustrate, under perfect competition and if firms' cost function $c(e,a)$ is separable in e and a, we will have $T_j(e,a) = e_j c_e + a_j c_a$ and $\frac{\partial T_j(e,a)}{\partial c_e} = e$. Under non-separability or imperfect competition, the pass-through could be smaller or greater than e. Our empirical strategy to determine $\frac{\partial \bar{e}}{\partial c_e}$ consists to first estimate $\frac{\partial \bar{e}}{\partial T_j(e,a)}$ using a simple demand system. Note that to implement our approach we need to estimate only one own-price elasticity and one set of cross-price elasticities with respect to the price of a single product. Therefore, a full demand estimation is not required. Second, we will treat $\frac{\partial T_j(e,a)}{\partial c_e}$ as a free parameter, which we will vary through sensitivity tests. Note that all previous studies that have estimated the degree of undervaluation to energy operating costs have had at least one free parameter. In our case, our free parameter characterizes the market conduct and the technology used to provide energy efficiency, i.e., whether or not the marginal cost of providing (e) is separable from the marginal cost of providing other attributes. In this framework, the quantification of size of the *Energy Efficiency Gap* has clear link between demand and supply, and explicitly accounts for the role of imperfect competition in the provision of energy efficiency.

Data

For this project, we have assembled several unique datasets. First, using transaction level data from a large appliance retailer, we have created an appliance-specific panel of aggregate energy demand, i.e., $\bar{e}$, at the county-week level for the period 2008 to 2012. To create this panel, we have created a weekly average of the expected energy consumption of all products in a given appliance category purchased at the retailer's stores present in each county. Our measure of energy consumption is the one reported by appliance manufacturers and presented on the EnergyGuide label. We collect data on nine appliance categories: full-size refrigerators, clothes washers, dishwashers, compact refrigerators, freezers, electric water heaters, air conditioners, clothes dryers, and electric ovens.

The above data do not identify the exact location of the customers making a purchase, only the location of the store. This somewhat limit our ability to control for region specific unobservables. Our second dataset overcomes this problem. We collect data from the Cash for Appliances program, which corresponds to all rebate claims made for Energy Star

products. This dataset identifies the zip codes of the customers and the manufacturer model number of the appliances purchased. This dataset covers the period 2010-2011.

Finally, our third dataset consists of local energy prices aggregated at the county-week level. These data come from the form EIA-861 of the Energy Information Administration, which provides information on revenues and quantity sold by each electricity utility operating in the US.

Preliminary Findings

Table 1 presents preliminary results for our cross-border estimator. For these estimations, we regress the annual energy consumption of the appliance model purchased (as reported by manufacturers) on average county-level electricity prices, and county-border fixed effects. As described earlier, a county-border fixed effect takes on the value of one for a county and each county that borders that county. Columns 1-3 display results for three appliance categories: refrigerators, dishwashers and clothes washers. In each case, the coefficient on local electricity price is negative and significant, indicating that consumers in counties with higher electricity prices buy appliances with lower annual energy usage than consumers in surrounding counties with lower prices. In our future research, we will extend our analysis to 6 more appliance categories and translate these reduced form estimates into an estimate of the share of inattentive consumers. Preliminary work with other estimators also suggests that local energy prices have a detectable effect on energy consumption.

TABLE 1. Estimation of the Effect of Local Electricity Price on Appliance Energy Use

	Refrigerators (kwh/year)	Dishwashers (kwh/year)	Clothes Washers (kwh/year)
local electricity price	-3.461^{**}	-5.837^{***}	-16.505^{***}
	(1.433)	(.4230)	(.7267)
constant	414.624	343.2137	394.3842
	(69255.02)	(19106.5)	(22254.49)
County-Border FE	Yes	Yes	Yes

Notes: The unit of observation is an appliance purchase. Local electricity price is the average energy price faced by consumers living in the county. The dependent variable is the annual energy consumption of the appliance model purchased in kwh/year. Standard errors are in parentheses. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels.

Disclosure Statement for: Quantifying Inattention to Local Energy Prices: A Novel Approach and New Evidence for Nine Appliance Markets

No other party will have the right to review the paper prior to its circulation. The authors have received no funding or significant financial support from the energy industry or other interested parties.

The transaction level data from the large retailer are proprietary. Micro-data will not be made publicly available. The panel dataset aggregated at the week-county level will be publicly available upon request.