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Are consumers attentive to local energy costs? Evidence from the appliance market ☆

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ABSTRACT

We estimate whether consumers respond to local energy costs when purchasing appliances. Using a dataset from an appliance retailer, we compare demand responsiveness to a measure of energy costs that varies with local energy prices versus purchase prices. We cannot reject that consumers respond to lifetime energy costs in the same way they respond to purchase prices under a wide range of assumptions. These findings run counter to the popular wisdom, which motivates energy standards, that energy costs are systematically undervalued due to various behavioral phenomena. They imply that electricity pricing that deviates from social marginal costs, due to failure to incorporate pollution externalities or due to other features in rate design, can have substantial distortionary effects on demand.

1. Introduction

Policymakers are increasingly relying on behavioral insights to design programs to alter consumer choices in ways that might improve market efficiency. Consumers make systematic mistakes in their choices for a wide range of products, such as health care plans (Abaluck and Gruber, 2011; Kling et al., 2012; Handel and Kolstad, 2015), mutual funds (Barber et al., 2005), schools (Jensen, 2010), and which foods to consume (Bollinger et al., 2011), among many others. Whether and how we should regulate markets when consumers are prone to mistakes has become an important and sometimes controversial topic (Allcott and Sunstein, 2015; Mannix and Dudley, 2015).

This paper asks how responsive consumers are to operating costs when purchasing household appliances. Policymakers have long argued that consumers undervalue energy operating costs, which has been the primary rationale for energy efficiency standards and energy labeling programs adopted in the 1980's in the U.S. and elsewhere (Hausman and Joskow, 1982). However, the Department of Energy (DOE) has had to set and periodically update federal minimum efficiency standards with little conclusive guidance as to whether and to what extent consumers actually undervalue operating costs.

Consumers' responsiveness to energy costs is a critical input for policymakers not only in setting appliance standards, but for understanding the impacts of policies that affect consumer electricity prices such as utility rate design and greenhouse gas (GHG) reduction policies. Borenstein and Bushnell (2018) demonstrate that in most parts of the U.S., electricity prices deviate substantially from the optimal social marginal cost. As a result, in large parts of the country where electricity rates already exceed social marginal costs, carbon prices would actually exacerbate the exist-

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ing distortion rather than being corrective. Crucially, how responsive consumers are to energy costs determines how distortionary are deviations from optimal pricing.

In the context of car markets, researchers have found that consumers are relatively attentive to local variation in gasoline prices (Allcott and Wozny, 2014; Busse et al., 2013; Grigolon et al., 2018), but much less attentive to fuel economy ratings (Gillingham et al., 2019) or the technology options determining vehicles' fuel economy (Leard et al., 2017). One important take-away from this literature is that different sources of variation in energy operating costs lead to different behavioral responses, and thus policy prescriptions. Therefore, it is critical for policymakers to consider consumer responsiveness to context-specific sources of price variation in policy design.

Our focus is in quantifying consumer responsiveness to local electricity prices—the policy-relevant variable for the impact of carbon pricing and its interaction with distortionary rate design in residential electricity markets. It is potentially difficult for consumers to be informed about how local electricity prices map into their operating costs (e.g., Auffhammer, 2017). For instance, it is not straightforward for households to attribute electricity costs to particular appliances given that they are billed for electricity monthly and that they are billed for their combined consumption across all end uses. Moreover, in the U.S., the mandatory EnergyGuide label for appliances prominently displays estimates of annual energy operating costs based on a national average of electricity price, which could induce consumers to ignore local electricity prices in their purchase decision (Davis and Metcalf, 2016).

In order to estimate consumer responsiveness to local energy costs, we use a unique administrative data set from a large national appliance retailer with individual transaction data on the timing and price paid for each model sold. We focus on consumers who purchase their own appliances, who are primarily homeowners. Since we know the location of each branch of the retailer, we can match county-specific annual electricity prices to each transaction. We focus on refrigerators, which offer two advantages. First, since refrigerators are plugged in continuously over their lifetime, it is straightforward to model operating costs, and abstract away from households' utilization decisions. Second, refrigerators consume a large amount of energy and there is rich variation in retail prices and expected energy consumption across models, which allows us to identify households' behavioral responses.

We employ a widely used test of consumer responsiveness: to compare the demand response to potentially misperceived costs (e.g. sales tax, shipping and handling fees, highway tolls, or energy operating costs), versus salient, correctly perceived purchase costs.[1] Unlike many demand estimation exercises, the pricing scheme of the appliance retailer results in variation in purchase prices that is plausibly exogenous to local market conditions. As we describe in detail in what follows, the retailer has a national pricing algorithm that induces model-specific idiosyncratic price variation. We exploit this variation and account for potential correlated demand shocks using a rich set of fixed effects. We estimate demand responsiveness to local energy operating costs using variation in relative operating costs among models driven by electricity price differences across utilities and over time. We show that these electricity price differences are largely driven by exogenous variation in the fuel costs. The fine grained nature of our data allow us to control for county-by-time specific movements in appliance demand, which allows us to disentangle the effect of energy operating costs on product choice from confounding market conditions which affect the probability of buying an appliance at all.

Counter to the popular wisdom, that local energy costs are a "shrouded" attribute of appliances (e.g., Auffhammer, 2017), we find that consumers are responsive to appliance operating costs. Our preferred estimates suggest that the subset of consumers that purchase their own appliances are close to indifferent between \$1.00 in discounted future energy costs and \$1.00 in purchase price. Further, for a wide range of lifetime and discount rate assumptions we cannot reject that consumers are fully attentive to energy costs. Consistent with previous work, we find that the valuation of energy costs relative to purchase price is somewhat negatively correlated with income (e.g., Hausman, 1979; Train, 1985). Given a discount rate assumption of 5%, we cannot reject full responsiveness to energy costs for consumers in the lowest and middle tercile of income, while the highest tercile appears to slightly over value energy costs. This suggests that consumers across the income spectrum are attentive to energy costs, but that a lower discount rate maybe appropriate for the highest income tercile. This could be due to differential access to credit and/or various behavioral phenomena.

Previous work quantifying consumer attention to appliance energy costs has been mixed, with some early studies finding that consumers substantially discount future energy costs (e.g., Dubin and McFadden, 1984; Hausman, 1979) and other more recent studies finding more modest undervaluation (e.g., Houde, 2018; Rapson, 2014). These studies have relied on variants of a discrete choice model and have exploited primarily cross-sectional variation in energy prices. While there is rich cross-sectional price variation in the U.S., it may be correlated with systematic differences in demographics or consumer preferences across regions, thus biasing these types of estimates.

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 little evidence that energy prices affect the market share of Energy Star appliances. The Energy Star certification is, however, an imperfect proxy for energy operating costs because the certification requirement varies with product class and is thus not perfectly correlated with energy consumption. Moreover, consumers may value Energy Star models for reasons other than energy savings (Newell and Siikamaki, 2017; Houde, 2018).

Our work thus provides the first estimates of consumer attentiveness to appliance energy operating costs by exploiting rich panel data. In the spirit of recent approaches in the context of cars and housing (e.g., Busse et al., 2013; Allcott and Wozny, 2014; Grigolon et al., 2018; Myers, 2019), we estimate average responsiveness with microdata which allows us to control for region-specific trends in preferences, removing many of the factors that might be correlated with electricity price that confound approaches using cross-sectional or more aggregated data.

These results also contribute to our understanding of electricity price demand response. Since consumers' appliance choices are affected by their local electricity prices, capital investments are an important margin to consider in designing energy and climate policies. To better understand the policy implications, we use our estimated demand model to simulate two scenarios that impact local electricity prices. First, we consider the effect of a national carbon pricing scheme where we increase county-level electricity prices to reflect the carbon externality (\$50/ton of $CO2$) from the local generation mix. Second, we consider the impact of a comprehensive electricity tariff reform that sets the county-level average variable charge equal to the optimal social marginal cost as calculated in Borenstein and Bushnell (2018). We find that the demand reduction from carbon pricing is large, on the order of 25%.[2] Con-

[1] See for example, shipping and handling fees (Hossain and Morgan, 2006), sales tax (Chetty et al., 2009), highway tolls (Finkelstein, 2009).

[2] This is comparable to the impact of the Energy Star certification—the U.S.'s primary appliance efficiency policy, which requires certified appliances to be at least 20% more efficient than the minimum standard. Note also that our estimates are calculated only for the area served by the retailer.

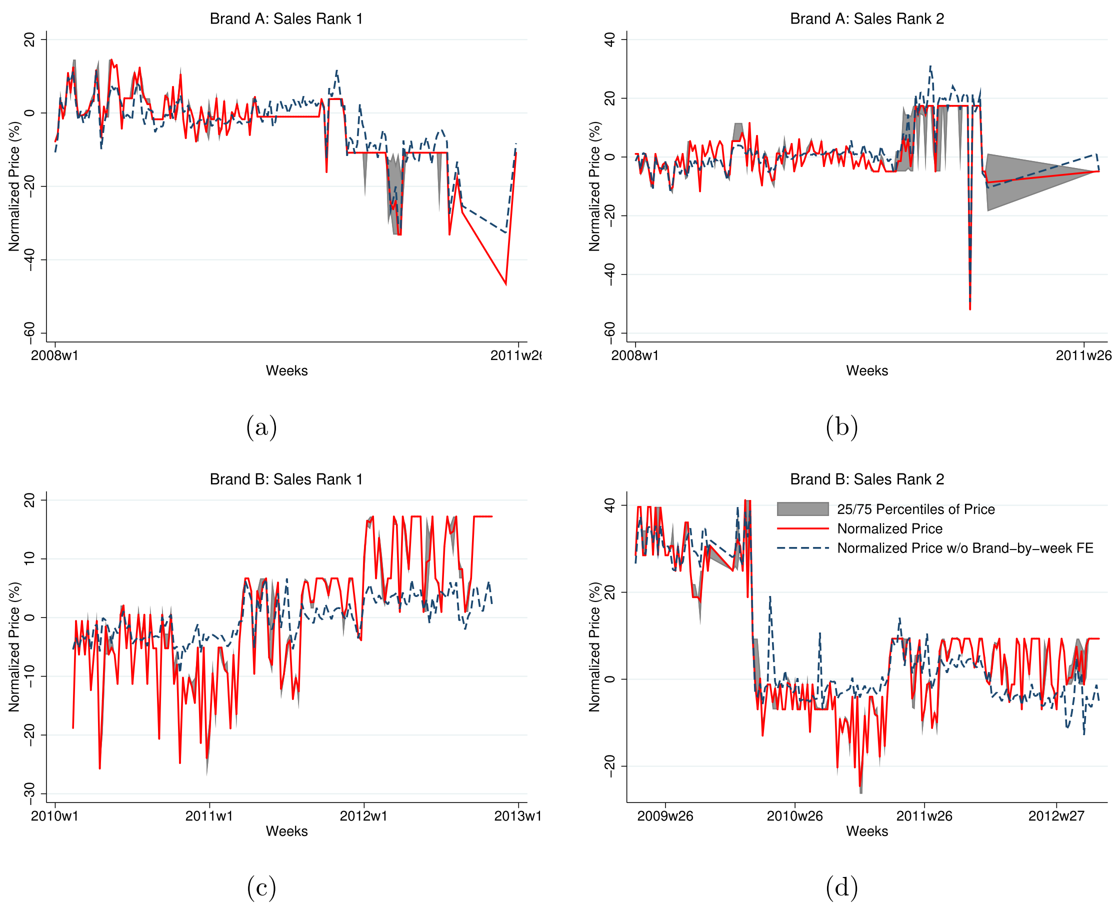

Fig. 1. Price Variation Due to Retailer's National Pricing Algorithm. *Notes*: Each panel corresponds to a particular model offered by a particular brand. Models with sales rank equal to one corresponds to the most popular model offered by a given brand. Each panel displays the week-to-week variation in retail price relative to the mean price for a particular model. The plain red line corresponds to the median price across zip codes. The grey band depicts the 25*th* and 75*th* percentiles. The dash blue line is the median price without brand-by-week fixed effects.

versely, when we set prices equal to social marginal cost it *increases* electricity demand from appliances by about 20%. This reflects the fact that in many parts of the U.S., existing electricity prices are well above social marginal costs (Borenstein and Bushnell, 2018). Taken together, these results suggest that existing rate distortions are of first order importance in considering the effects of climate policy on demand for durables. The substantial rate increases from carbon policy combined with a strong behavioral response to energy costs can exacerbate existing distortions.

This paper proceeds as follows. Section 2 describes the data, Section 3 details the empirical framework, Section 4 describes the estimates of consumer inattention to energy operating costs, Section 5 conducts a policy analysis, and Section 6 concludes.

2. Data

We use transaction level data from a major U.S. appliance retailer, which includes all transactions for 2008–2012 that involve full-size refrigerators. The data for each transaction includes price paid, zip code of the store location, refrigerator model number, and an identifier tracking consumers making multiple purchases with the same credit card. During the sample period, we observe several million refrigerator purchases across stores located in most U.S. states. For our analysis, we first exclude online sales, which represent a small fraction of the sales during the sample period. We also exclude purchases made by renters, which is also a small percentage ($< 2\%$). Finally, we restrict the sample to transactions where we observe only one purchase of a full-size refrigerator by household identifier. This corresponds to approximately 68% of the sample. The latter criterion is a conservative way to identify transactions made by households in the sample. Our goal in creating this restricted sub-sample is to exclude transactions made by contractors, landlords, renters, or governmental entities that may be subject to different incentives when investing in energy-efficient appliances. For example, they may not have to pay for the electricity operating costs of the appliances they purchase.

The purchase price we use in our analysis is the actual retail price paid by the consumer. We also observe the manufacturers' suggested retail prices, sales taxes paid on each transaction, and an indicator variable that specifies whether the retail price paid for a particular transaction corresponded to a promotional price. An important institutional feature that we exploit in our empirical strategy is the fact that the retail prices are determined by the retailer at the national level using a pricing algorithm. The pricing strategy thus results in rich variation over time and appliance models but not across stores. Due to this algorithm, the price of each refrigerator model is also subject to weekly variation, which is model specific and not perfectly correlated within brands.

Fig. 1 shows the idiosyncratic variation that the pricing algorithm induces. Each panel plots a time series of retail prices for four different models. For the purpose of illustration, we focus on the two most popular models of two different brands. Though, the pat-

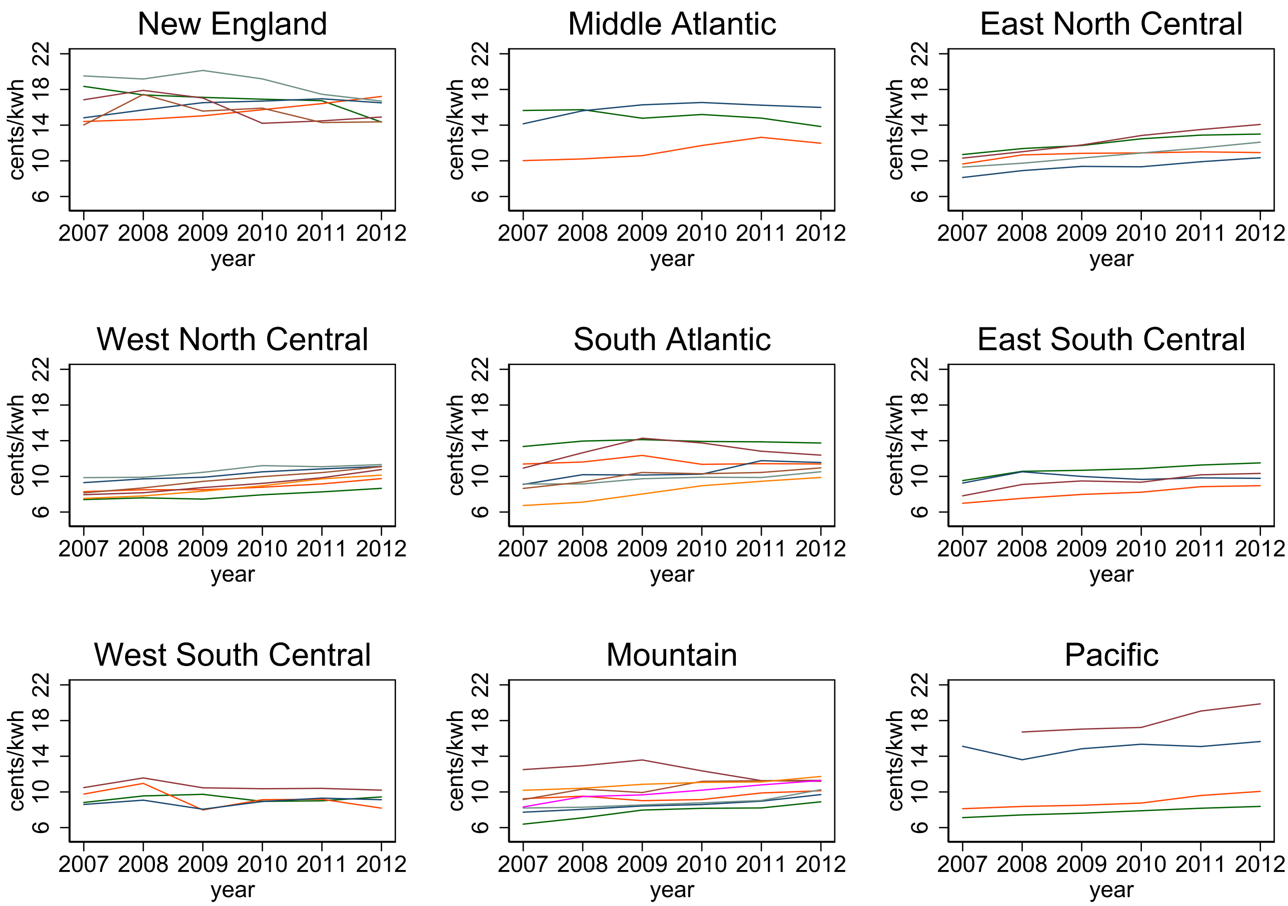

Fig. 2. Average Electricity Prices for Each State in a Census Division. *Notes:* Each line represents the appliance sales weighted average electricity price for a particular state within each census division.

terns are similar across other models and brands. To create the figure, we aggregated data to the model-week-zip code level. We first normalized retail prices by removing model-specific fixed effects. We then computed the median, the 25*th* percentile and the 75*th* percentile at the model-week level. The goal of comparing these three time series is to show that, because of the national pricing strategy, there is little variation across regions for a given model. This is confirmed by the fact that the 25*th* and the 75*th* percentiles exactly coincide with the median retail prices for most weeks—i.e., there is no variation across regions. Variation over time is, however, important. From week-to-week, we see price changes of the order of 10%. Another important takeaway from Fig. 1 is that the rich weekly variation appears not to be correlated within brand. We show this formally with the blue dashed line that corresponds to the normalized price conditional on week-of-sample fixed effects interacted with brand dummies. These fixed effects remove all time-varying and brand-specific demand shocks at the national level. The fact that these residual prices closely follow the normalized price of each model confirms that the pricing algorithm induces rich model-specific price variation within brands.

Further, the price variation is also independent of demand shocks for particular refrigerator features. In Table 2, we show the change in price with respect to the mean after controlling for not only brand-by-week fixed effects, but also Energy Star-by-week fixed effects, and other attribute-by-week fixed effects (i.e. size-by-week, and freezer location-by-week fixed effects). These various controls remove little variation compared to the variation observed in normalized prices. This suggests that the pricing algorithm provides credible exogenous variation in retail prices, which is uncorrelated with shifts in demand.

We create a measure of annual energy cost for each refrigerator purchase using the manufacturer reported annual kWh consumption multiplied by the county-level annual average electricity price. We construct county-level electricity prices using Energy Information Administration (EIA) form 861, which reports revenue and quantity of electricity consumed by residential consumers. Form 861's revenue measure is inclusive of taxes, fuel charges, and capacity and transmission charges. We divide revenue by quantity sold to create a measure of average electricity price for each utility operating in the U.S. The EIA also provides information on which utilities serve each county, allowing us to map average energy prices to the county level. If a county is served by more than one utility, we take a sales-weighted average of the prices for each utility serving that county.

In our estimation, we exploit variation in the relative energy operating costs among models coming from electricity price differences across utilities as well as changes in prices over time. Areas with higher electricity prices at particular points in time will have larger differences in relative operating costs than places that have lower electricity prices at particular points time. Figs. 2 and 3 give a sense of this variation. Fig. 2 shows the mean sales-weighted annual electricity price for each state in a U.S. census division. Each of the 9 plots represents a U.S. census division and each line on the plot represents a state in that census division. It is clear from this figure that prices vary quite a bit regionally, with the highest prices in New England (above $0.15/kwh on average) and lowest prices in the Midwest and the South (less than \$0.10/kwh on average). There is also variation in prices over time, where some states experience increases over the study period, while others experience decreases.[3]

Fig. 3 displays density plots of prices and lifetime energy costs. The first panel shows the distribution of prices paid in our sample. Almost all models sold are less than \$2000, though there is some density for high price models ($> \$5000$). The second panel shows how the distribution of life time energy cost of the models sold vary across places with higher or lower electricity prices. We display the distribution for the 10th, 50th, and 90th percentile of electricity price. To calculate lifetime cost, we sum over an expected lifetime of 12 years, using a 5% discount rate.[4] Mean lifetime costs vary from \$437 for the 10th percentile of energy price to \$786 for the 90th percentile. The third panel displays the distribution of the ratio of lifetime cost to purchase price. The mean ranges from 0.35 at the 10th percentile of energy price to 0.62 at the 90th percentile. Therefore, operating costs are a significant fraction of the lifetime costs of the appliance.

In the U.S. appliance market, another potential determinant of purchases of energy-efficient appliances are consumer rebates for models that are certified by the Energy Star program. During the sample period, two types of Energy Star rebates were offered. First, several electric utilities offered rebate programs as part of their demand-side management portfolio. The DSIRE database collects all information about utility rebate programs. Using these data, we identified all rebate programs that apply to full-size refrigerators and constructed time series of utility rebates at the county-year level. Utility rebate programs were present in 129 different counties during the period 2008–2012. In those counties, the rebate amount ranged from \$10 to \$250, with a mean of \$74. In addition to utility rebate programs, state governments also offered rebates for Energy Star products during that period. The State Energy Efficiency Appliance Rebate Program (SEEARP) was funded as part of the stimulus package of the American Recovery Act. This program led to generous rebates for Energy Star certified products from 2010 through 2011. Houde and Aldy (2017) collected data on the level and timing of the rebate programs offered by each state, which we use for this analysis. In several states, these programs were short-lived and lasted a few weeks, and even a few days in some rare instances. We thus constructed measure of SEEARP rebate at the state-week level. These rebate programs have substantial variation across states and time—44 states offered a rebate targeting full-size refrigerators with a mean rebate amount of \$128.

For our main analysis, we aggregate the transaction level data at the model-week-zip code level. Note that for most zip codes, there is only one retail store. For each appliance model, we create time series of sales and retail prices. We do not observe store inventories, and not all models sell in every zip code in every week. We impute choice sets using the first and last sales of each refrigerator model in each location (i.e., zip code). That is, we assume that this model was available between those two sale events period at this particular location. The time series of sales have a large number of zeros, which correspond to weeks where a model was available but did not sell. The overall sample used for the estimation is a 50% sample of the universe of qualifying transactions and has 9,363,591 unique combinations of refrigerator models, weeks, months, and zip codes. We observe 2,492 different models during the period 2008–2012. Table 1 provides summary statistics for the main variables used in our estimation.[5]

One takeaway from Table 1 and the above analysis is that there is ample variation in the key variables we use for our estimation, namely retail prices and electricity costs. One concern is that this heterogeneity is driven by variation in product offering across stores. However in the Appendix Table C.2, we show that this is not case. The variation within store is closely in line with the one we report in Table 1, which is across the whole sample. Each store offers a large number of models, 145 on average (sd = 68), which leads to this variation. But even if we restrict the sample to only the two most popular models offered in a store (in a given trimester), we still find substantial variation within store. Our identification thus relies on within choice set variation, which is key for our empirical strategy.[6]

3. Empirical Strategy

The starting point of our empirical strategy is based on a discrete choice model. Utility of consumer i for product j in county c in zip code z and time t is given by:

$$U_{ijczt} = \eta P_{jczt} + \theta E_{jct} + \gamma_j + \xi_{ct} + County_c \times Att_j + \phi Rebate_{jct} + Brand_j \times Week_t + \epsilon_{ijczt} \quad (1)$$

where P_{jczt} is the purchase price and E_{jct} is the annual operating cost (\$/year). The coefficients on these two variables, η and θ respectively, are the quantities of interest. Our energy cost data for a particular product vary by county-year (the level of variation of our average electricity price data). For the estimation, we compute E_{jct} as the annual operating energy cost of product j, which is the annual kWh consumption reported by the manufacturer, multiplied by the county average electricity price in a particular year.

The unobservable portion of utility is represented by ϵ_{ijczt}. We assume that consumers choose the option that gives them the highest utility among their choice set in county c and zip code r and time t and that ϵ_{ijczt} is i.i.d. extreme value distributed, which gives rise to the conditional logit. The other components are controls, which, as we explain below, each play a particular role for our identification.

Product fixed effects are denoted by γ_j and capture time-invariant preferences for each product that are common to all consumers. Thus, we exploit time and regional variation in purchase prices and annual operating costs within product. The term ξ_{ct} represents county-by-year fixed effects. These fixed effects capture

[3] See Appendix B for plots of the cross-sectional relationship between purchase share above median efficiency and price.

[4] The Department of Energy (DOE) uses a 5% discount rate and 17.4 year lifespan in setting appliance standards according to their 2011 revision of refrigerators' minimum standards (EERE, 2010). However, estimates based on home inspections and surveys of consumer beliefs by consumer advocacy and trade association groups report shorter lifespans ranging from 9 to 13 (e.g., the National Association of Home Builders (National Association of Home Builders/Bank of America NAHB, 2007), the International Association of Certified Home Inspectors (The International Association of Certified Home Inspectors NACHI, 2020) and the Consumer Reports (Consumer Reports, 2019). These estimates likely better reflect what consumers experience when they purchase a refrigerator. Note that in our empirical test of consumers' valuation, a lower value of the expected lifetime provides a more conservative test of full valuation.

[5] The price variable that we use in our regressions is the weekly retail price inclusive of all local sales taxes. The sales tax rates are computed using our data and correspond to zip code-yearly averages. For our estimation, we drop 1,241 observations ($> 0.01\%$ of the sample) without information about sales taxes.

[6] Another takeaway from Table C.2 is that there is heterogeneity between stores. However, in Table C.3, we show that the product assortment of each store has a weak correlation with local electricity prices. In each column we regress a measure of store-level assortment on local electricity price. The measures of store-level assortment include the average, min, max, and range of annual kWh for products offered, average efficiency level, average size, and average retail price. Once we account for state-level unobservables, we detect no correlation between the characteristics of the products offered in a local store and the corresponding county-level electricity price. To further test this assertion, we run our preferred specification (described in the following section) with an additional control for assortment size and show that correlation between product characteristics and local energy price do not appear to be a biasing factor in the estimation (See Appendix Table C.4).

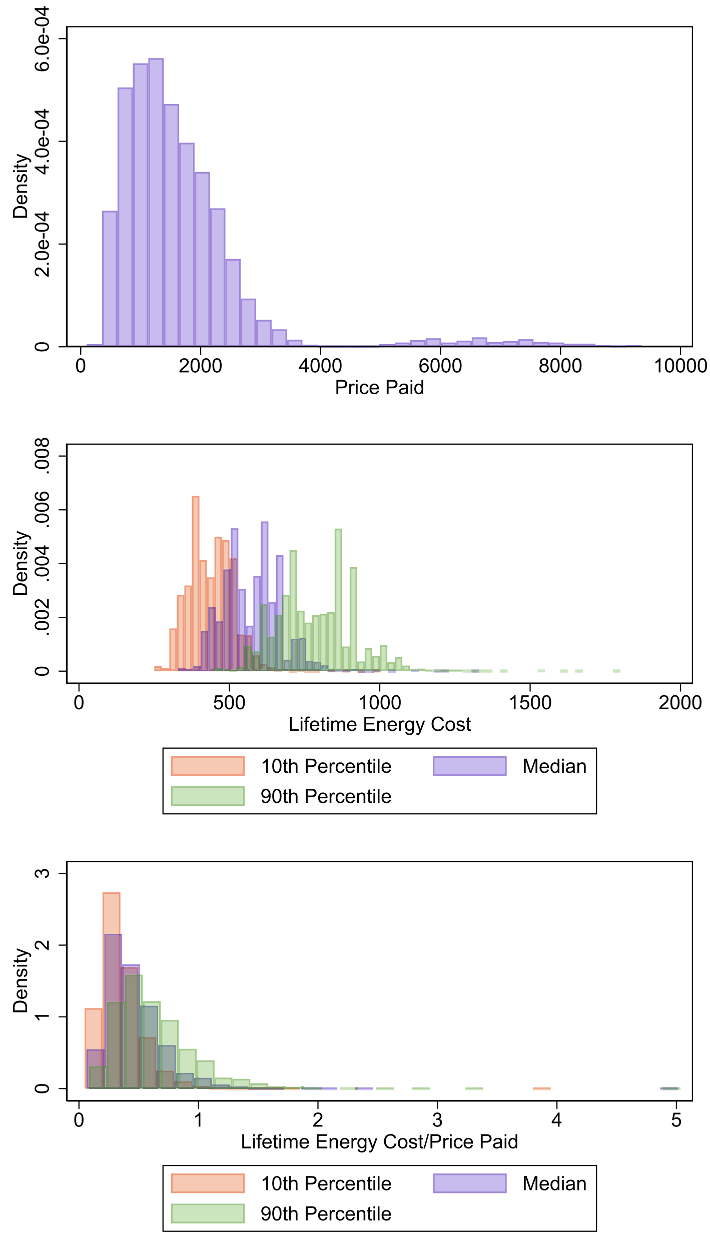

Fig. 3. Distributions of Prices and Lifetime Energy Costs. *Notes:* The lifetime energy costs are calculated using, an expected lifetime of 12 years, and a discount rate of 5%, and the manufacturer's reported annual energy consumption for each model at the 10th, 50th, and 90th percentile of electricity prices.

Table 1
Summary Statistics: Main Sample.

	Mean	S.D.
Retail price ($)	1263.26	620.15
Retail price inclusive of sales taxes ($)	1348.87	662.63
Sales (qty/model-week-zip code)	0.26	0.59
Electricity operating costs ($/year)	63.01	20.35
kWh/year	508.85	76.50
Share of refrigerators $<$ 29 cu. ft. (%)	54.69	49.77
Energy Star-certified (%)	76.27	42.54
Share of top-freezer (%)	29.09	45.42

Notes: Summary statistics (mean and standard deviation) for the main variables used in the regressions. The overall sample used for the estimation has 9,363,591 unique combinations of refrigerator models, weeks, months, and zip codes. The sample has 2,492 unique refrigerator models during the period 2008–2012. Electricity operating costs are computed by multiplying average electricity prices at the county level and manufacturers' reported estimates.

local trends affecting the retailer, including preferences for the outside option.

Because the electricity price variation in the model is at the county-year level, the remaining variation in annual operating cost after including, ξ_{ct}, comes from the relative energy cost differences among products in a given county in a given year, where the relative energy cost differences will be larger in counties with high electricity prices than in counties with low electricity prices. In other words, the shifts in local electricity prices can be thought of as changes in treatment intensity, where higher electricity prices create larger differences in relative operating costs. Therefore, we are estimating effect of energy operating costs on product choice while controlling for confounding market conditions affecting the probability of buying an appliance at all.

One concern with the variation in relative energy costs we are using in our model is that preferences for energy-related attributes are correlated with local electricity prices. This correlation may

Table 2
Idiosyncratic Variation in Retail Prices.

	(1)	(2)	(3)	(4)	(5)	(6)
Δ Price w.r.t. Mean Price (%)	9.39	8.05	7.89	7.40	7.06	6.77
R^2	0.965	0.973	0.974	0.977	0.979	0.980
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	No	Yes	No	No	No	No
Brand × Week FE	No	No	Yes	Yes	Yes	Yes
EStar × Week FE	No	No	No	Yes	Yes	Yes
Attribute × Week FE	No	No	No	Yes	Yes	Yes
County × Product FE	No	No	No	No	Yes	Yes
County × Brand × Week FE	No	No	No	No	No	Yes

Notes: The dependent variable is the log of the retail prices. Each column reports the standard deviation of the residuals of a regression of the log of retail prices on various fixed effects. These residuals correspond to the percentage variation in retail prices relative to the mean price of each refrigerator model, which we denote Δ Price w.r.t. Mean. The attributes other than Energy Star (EStar) that we consider are a dummy variable that identifies small versus large full-size refrigerators and a dummy variable that distinguishes top-freezer versus other types of refrigerators.

arise for a variety of reasons. High income households might prefer larger refrigerators and live in regions subject to higher electricity prices. Moreover, in regions with high electricity prices such as New England and California, electric utilities, retailers, and local governments may advertise energy-efficient products more, especially Energy Star-certified products.

In order to control for region-specific preferences for energy-related refrigerator features we interact county dummies with a rich set of refrigerator attributes that induce the vast majority of the variation in energy use across models ($County_c \times Att_j$). Specifically, we interact county dummies with: (1) indicators for model type (i.e. top freezer, side by side refrigerator, or bottom-freezer), (2) an indicator for above mean fridge size (adjusted volume above 29 cu. ft.) (3) an indicator for Energy Star certification, and (4) indicators for each of the 10 brands in our sample. We show in Table A.1 in Appendix A that these four types of indicators explain 85% of the variation in annual kWh consumption across models, where the indicators for type and size alone explain almost 70% of the variation.

We also control for rebates offered for Energy Star certified products ($Rebate_{jct}$), which may make products more attractive. Rebates vary across regions and time, and thus capture time-variant demand for certified products that is not captured by the refrigerator attribute-by-county fixed effects.

Finally, we also control for brand-by-time fixed effects. As previously shown in Fig. 1, the variation in purchase price is idiosyncratic and model specific. Nonetheless, there is some correlation across models within brand—if we look at the variation in prices after controlling for brand-by-week fixed effects (the dashed blue line on Fig. 1), some, but not all, model-specific variation is smoothed out. The brand-by-week fixed effects thus allow us to control for brand-specific marketing activities that might be correlated with weekly promotions.

Our discrete choice model provides the micro-foundation for describing the number of units sold for a particular product as a function of purchase price, energy operating costs and these detailed controls. Sales of product j in county c, zip code z and time t, y_{jczt}, corresponds to the choice probabilities multiplied by the local market size (county - zip code cz and time t). We assume that sales follow a Poisson distribution and estimate the model with a Poisson regression. Thus, the right-hand-side of Eq. 1 corresponds to the log of the conditional mean of sales (i.e., $log(E[Y|X])$). For our estimation, we aggregate our transaction data to the model-week-zip code level. Not all products sell every week in every zip code, so there are a large number of zero sales in our dependent variable.

Poisson regressions offer several advantages for our context. First, as demonstrated by Guimaraes et al. (2003), the coefficients that we obtain from a Poisson regression correspond exactly to the coefficients of a conditional logit model given that none of our regressors are consumer-specific. Therefore, our estimates are fully consistent with the discrete choice model outlined above. Second, like OLS, which is consistent and asymptotically normal even if the normality assumption is violated, Poisson has the nice property that quasi-maximum likelihood estimation recovers consistent, asymptotically normal coefficient estimates even if the Poisson distribution does not hold (Wooldridge, 2010). Third, unlike other discrete choice models, e.g., conditional logit and negative binomial, we are able to efficiently estimate models with high-dimensional fixed effects using the algorithm proposed by (Guimaraes and Portugal, 2009).

3.1. Robustness checks

In addition to our main specification, we perform several other estimations to probe the robustness of our results: 1) a sensitivity analysis to the inclusion of a number of fine-grained fixed effects that capture shifts in demand and consumer demographics; and 2) two instrumental variables approaches to address measurement error in energy costs.

First, we consider the role of longer-run drivers of demand. The Great Recession occurred during the sample period and led to significant changes in demand for products across the economy. Therefore, we include county-by-year-by-indicator for above median purchase price fixed effects. These controls account for a drop in demand for high-priced products that different counties may have experienced during the recession.

We also consider the role of shorter-run drivers of demand. As mentioned above, if the retailer's national pricing is determined by aggregate shifts in demand for particular models or types of appliances, it could potentially bias our estimates. Product assortment in each store could also respond to short-run changes in demand, which could also impact our estimates. In order to explore this possibility, we estimate a model that includes attribute-by-week fixed effects. In particular, we interact Energy Star status, the indicator for fridge size, and indicators for model type each with week fixed effects. These fixed effects will capture trends in demand for particular model features.

Additionally, shifts in demand could also be driven by trends in the types of customers at the retailer driven by local market conditions such as competition between different retailers. To address these types of shifts in demand, we estimate a model with zip code-by-week fixed effects. If most of the variation in the retailer's pricing algorithm is driven by shifts in demand for particular features or substitution across retailers, inclusion of attribute-by-week fixed effects or zip code-by-week fixed effects will soak up a lot of the variation in purchase price and affect the coefficient estimates of η. If η changes little, it is suggestive that the variation in the national pricing algorithm is driven by supply-side or other idiosyncratic drivers, which are exogenous to local market conditions.

It could be that selection operates in a more subtle way and there is correlation in preferences between particular consumer demographics and specific products, which could also bias our coefficients. To explore this possibility, we use demographic information that is available for a large subset of transactions. For those purchases, we use an individual identifier to match purchases with household demographics collected by a data aggregator. Demographic information includes household income category, age of head of household, number of adults and children in the household, and educational attainment of head of household. We calculate median measures of each of these demographics at each zip code for every week in the sample. Then, we estimate the model using demographic-by-product FE to control for any time-invariant correlation in preferences between particular consumer demographics and specific products. If the estimates of η and θ change little with these controls, it shows that it is unlikely that the variation identifying our coefficients is due to variation in the types of customers at the retailer.

We next consider two instrumental variables approaches for addressing measurement error in the energy cost variable. Recall that the energy cost variable (E_{jct}) for product j in county c in year t is the product of the *average* annual county-level electricity price (C_{ct}) and the manufacturers' reported annual kWh consumption (kWh_{jt}). There are several potential sources for measurement error in the annual energy cost variable. First, using the average annual county-level electricity price to construct the energy cost measure may lead to measurement error if consumers are instead responding to their individual *marginal* electricity price, as economic theory would predict.[7] Specifically, it would bias our estimates of annual energy costs up and thus attenuate our estimates of consumer responsiveness to energy efficiency.[8]

Second, there may be measurement error in using the manufacturers' reported annual kWh consumption as a measure of efficiency if consumers responding to something different about a product's energy cost. For example, they may be responding to the fact that a product is broadly energy efficient or inefficient even if they do not know the exact efficiency. This type of measurement error could also bias our estimates of consumer responsiveness to energy efficiency.

We construct two instrumental variables to address measurement error in each of these aspects of energy cost. First, we construct an instrument aimed at the electricity price component of annual energy cost. Following Kahn and Mansur (2013) we create a capacity-weighted average fuel price for each utility-year by summing over the product of the utility's capacity shares of coal, oil and gas-fired power plants and their respective annual average fuel price. The intuition behind the validity of these instruments is that the identifying variation in local electricity prices is coming from the underlying fuel price variation, which is driven by national and global economic trends, rather than by county- or state-specific policies. Therefore, the only way fuel price variation can affect local appliance selection is through higher or lower electricity prices due to the pre-determined generation mix. Given that the generation mix in a given region is determined by long-term capital investments, it is likely exogeneous once we control for county fixed effects.

To construct the instrument, we use data from EIA form 860 to obtain the shares corresponding to the generation mixes. We use shares from 2007, the year before our sales data begin, so that their values are pre-determined. We use the crude oil WTI spot price for petroleum plants and the annual Henry Hub contract 1 prices for natural gas plants. For coal plants, we use the national average coal price from EIA. We then calculate a single generation-weighted fuel price, F_{ct}, for each county-year by averaging prices across any utilities serving that county. The instrument for a product's county-level electricity cost, $\widetilde{E}_{jct}$, is then the product of the generation-weighted fuel price and the manufacturer's reported kWh/year: $\widetilde{E}_{jct} = F_{ct} \cdot kWh_{jt}$. The first stage for the instrument is as follows.

$$E_{jct} = \eta P_{jczt} + \gamma \widetilde{E}_{jct} + \phi Rebate_{jct} + \gamma_j + Brand_j \times Week_t + County_c \times Att_j + \xi_{ct} + \upsilon_{jczt}. \tag{2}$$

Second, to address issues of measurement error due to consumers' perceptions of energy efficiency, we use an approach that is akin to the grouping estimator used in Allcott and Wozny (2014). We group products according to whether they have above or below median manufacturer reported consumption for their type (i.e., top freezer, side-by-side refrigerator, or bottom freezer).[9] We calculate the mean manufacturer reported kWh consumption for each of these 6 groupings–two efficiency categories for each of three types–for each year in the sample ($k\bar{W}h_{gy}$). We then construct an instrument for a product's energy costs as the product of the group mean consumption and the county-level average annual electricity price ($\overline{E}_{jct} = k\bar{W}h_{gy} \cdot C_{ct}$). The first stage for this approach is then identical to Eq. 2, except the instrument is $\overline{E}_{jct}$ rather than $\widetilde{E}_{jct}$.[10] Grouping in this way retains the fundamental identifying energy cost variation, which comes from the interaction of product efficiency and electricity price. Using group level aggregation could better represent consumers that may be responding to whether a product is broadly efficient or inefficient, but have some error in their perception of exact energy costs.

3.2. Interpretation of model parameters

The empirical test of consumer responsiveness in this paper asks how consumers trade off purchase price with energy costs. Absent any bias, consumers would be indifferent between an additional dollar of purchase price and an additional present discounted dollar of energy expenditure. Consumers may undervalue energy costs at the time of purchase relative to what would be privately optimal due to what Allcott and Greenstone

[7] There is strong evidence that consumers are more responsive to average rather than marginal price in the context of steeply increasing-block pricing in California (Ito, 2014). However, outside of California, this type of mistake is likely less relevant given that pricing schedules are much flatter (Borenstein and Bushnell, 2018). There, the difference between average and marginal price is largely driven by the presence of recurring monthly fixed charges. Understanding and distinguishing this type of charge from the marginal price is more straightforward than predicting where one will end up on an increasing-block schedule at the end of the month (Ito and Zhang, 2020).

[8] Another potential source of measurement error is that we use the average county price of the county in which the appliance was purchased, which may differ in some cases from the county in which the consumer lives. In Appendix C, we investigate the role of this type of measure error by: (1) examining the effect of using state-level average prices, which may differ from county-level prices in terms of measurement error and (2) estimating our model limiting our sample to those counties that are served by only one utility, so that our average energy price is not subject to this type of measurement error for everyone living in that county.

[9] We distinguish the type of refrigerator with respect to the freezer location because it is the main determinant of overall energy use for full-size refrigerators (see Table A.1) and plausibly an attribute that consumers consider early in their search process.

[10] Allcott and Wozny (2014) use indicators for over 200 groupings (above or below median efficiency for each month in their sample) as instruments for car efficiency. Since our variation is at the county-by-product-by-year level, an equivalent approach would require a much larger set of group-indicators as instruments and would be computationally intensive. Therefore, we instead construct a single instrument of group-level averages, which is directly analogous to Allcott and Wozny (2014), since their second stage fitted values are essentially group-level averages.

(2012) defined as "investment inefficiencies." These inefficiencies may encompass various behavioral phenomena such as inattention, myopia, imperfect information, biased beliefs and/or frictions due to credit constraints. Our empirical strategy does not allow us to take stance on which investment inefficiencies are at play in our context. Rather, our goal is to test whether such inefficiencies, in aggregate, lead to an under- or over-valuation of energy costs in the appliance purchasing decision.

The coefficient on annual energy cost, θ, reflects how a $1 change in annual energy operating costs affects sales, or more specifically the probability of a purchase. We measure consumer responsiveness as the ratio between the effect of a $1 change in *lifetime* energy operating costs on demand and the effect of a $1 change in purchase price. In order to estimate lifetime operating costs, we need to make assumptions about: 1) how consumers sum and discount future operating costs, 2) consumers' expectations about future annual operating costs, 3) the lifetime of the appliance, and 4) consumers' discount rate.

One feature of our approach is it is straightforward for analysts to apply different assumptions for the lifetime cost parameters to judge consumer bias based on our reduced form estimates of consumer responsiveness to price and energy costs. Other analysts can readily take our estimates, make alternative assumptions, and calculate the resulting valuation ratio estimates. In what follows, we describe our preferred parameter assumptions and the range we consider around them for sensitivity analysis.

For our analysis, we assume that consumers discount future costs using the exponential model of intertemporal choice and believe prices follow a random walk so that today's prices are the best predictor of tomorrow's prices.[11] As mentioned before, we use 12 years for the lifetime of the appliance and 5% for the discount rate. We also show sensitivity of our responsiveness measure to lifetimes of 10, 12, 15, and 18 years and discount rates ranging from 2% to 10%.

Assuming that consumers form time-invariant expectations about the annual operating electricity expenditure, the lifetime energy operating cost (LC_j) for the durable j is given by:

$$LC_{jct} = \sum_{t=1}^{L} \rho^t E_{jct},$$

where L is the lifetime of the durable (e.g., 12 years), $\rho = 1/(1+r)$ is the discount factor with discount rate r, and E_{jct} is the product of the electricity price paid by a household in county c at time t and the manufacturer's expected annual electricity consumption for durable j. If consumers have time-invariant expectations about the annual energy costs, i.e., $E_{jct} = \widehat{E}_{jc}$, the lifetime energy operating cost of product j is given by:

$$LC_{jct} = \rho \cdot \left(\frac{1-\rho^L}{1-\rho}\right) \cdot \widehat{E}_{jc}, \tag{3}$$

where we use the formula for a geometric series to express the summation analytically. If consumers value one dollar in lifetime energy operating cost the same way that they value one dollar in purchase price, the response to energy operating costs should be: $\eta \cdot \rho \cdot \left(\frac{1-\rho^L}{1-\rho}\right)$. If this is true, the coefficient that we estimate on annual energy costs would be equal to this term as follows.

$$\theta = \eta \cdot \rho \cdot \left(\frac{1-\rho^L}{1-\rho}\right). \tag{4}$$

The ratio of these two terms, known as the "valuation ratio," is then a measure of the average degree of consumer responsiveness to energy costs (Allcott, 2013):

$$m = \frac{\theta}{\eta \cdot \rho \cdot \left(\frac{1-\rho^L}{1-\rho}\right)}. \tag{5}$$

A ratio of one implies that consumers trade off $1 in purchase price that exact same way they trade off $1 in discounted lifetime energy operating cost. Therefore, if we reject the hypothesis that $m = 1$, it is indicative of the presence of investment inefficiencies in the valuation of energy costs. Specifically, $m < 1$ suggests consumer undervaluation of energy costs.

4. Results

4.1. Main estimation

Table 3 displays the results from the estimation of our main specification. Columns 1 through 3 show the impact of additional controls, where Column 4 corresponds to our preferred specification described in Section 3. Rows 1 and 2 display the coefficient estimates for product price and annual energy costs. The bottom panel displays the estimate of the valuation ratio (m) using a 5% discount rate and an expected lifetime of 12 years. The last row of the table reports the p-value of the hypothesis test that the valuation ratio is equal to one under the null. All specifications control for product fixed effects, Energy Star certification status, and Energy Star rebates.[12] Standard errors are clustered at the county level.

The first column shows the results from an estimation including county fixed effects and week-of-sample fixed effects and the second column shows results from an estimation with county-by-year fixed effects, and with similar controls otherwise. When county fixed effects are not interacted with a time dimension, the coefficient on energy costs is statistically significant, but suggests a large degree of undervaluation of energy costs, where $m = 0.316$. These results are consistent with previous findings that consumers are not very responsive to local energy prices in appliance markets using cross-sectional or more aggregated panel data.

In Specification 2, the coefficient on energy costs is more than three times larger than in Specification 1, and $m = 1.04$. The large difference between Specifications 1 and 2 suggests that variation in local energy prices potentially has important correlations with local market conditions, which affect refrigerator demand. Models controlling for county fixed effects uninteracted with time confound the effect of energy cost on appliance choice with its effect on the probability of buying an appliance at our retailer at all.[13]

The estimation in column 3 includes brand-by-week-of-sample, instead of only week-of-sample, fixed effects. This has a small impact on the coefficient of purchase price and the average measure of responsiveness, which suggests that the model-specific variation in purchase price is not strongly correlated with brand-level strategies, as we previously demonstrated in Section 2.

[11] Anderson et al. (2013) finds that consumers believe that gasoline prices follow this type of pattern. Another possibility is that consumers use information from futures markets to make projections about electricity prices going forward. However, forward curves rarely deviate substantially from spot prices for major generation fuels. Therefore, even if consumers were paying attention to trends in futures prices, their beliefs about fuel prices going forward would not differ significantly from no-change beliefs (Myers, 2019).

[12] The dummy for the Energy Star status has within model variation due to the fact that a large number of models lost their certification status in April 2008 due to a revision of the requirement.

[13] We find that county-by-year fixed effects are sufficient to capture these confounding local effects. In the Appendix C (Table C.1, Specification 1), we show that including county-by-week fixed effects rather than county-by-year fixed effects produces similar results to our preferred specification. In Appendix D Table D.1, we also replicate Table 3 using zip code-by-year fixed effects and zip code-by-attribute fixed effects rather than county-by-year or county-by-attribute.

Table 3
Estimation of the Effect of Price and Energy Costs on Demand.

	(1)	(2)	(3)	(4)
Purchase Price	−0.219***	−0.224***	−0.222***	−0.226***
	(0.00352)	(0.00348)	(0.00360)	(0.00330)
Annual Energy Cost	−0.611***	−1.990***	−1.977***	−2.074***
	(0.0609)	(0.158)	(0.158)	(0.177)
<u>Fixed Effects</u>				
Product	Yes	Yes	Yes	Yes
County	Yes	Yes	Yes	Yes
Week	Yes	Yes	Yes	Yes
County × Year	No	Yes	Yes	Yes
Brand × Week	No	No	Yes	Yes
County × Efficiency Attributes	No	No	No	Yes
Observations	9259311	9259311	9257787	9255983
Valuation Ratio	0.316	1.005	1.003	1.037
	(0.032)	(0.080)	(0.081)	(0.087)
<u>Test valuation ratio = 1</u>				
P-value	0.0000	0.9548	0.9720	0.6655

Notes: Each model is estimated using a Poisson regression. The dependent variable is the number of units of a particular refrigerator model sold in a given week in a given zip code. The standard errors are clustered at the county level and are in parentheses. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels. The Purchase Price and Annual Energy Cost variables are in hundreds of dollars. The valuation ratios are computed assuming a discount rate of 5% and a refrigerator lifetime of 12 years.

In our preferred specification, column 4, we include county fixed effects interacted with the Energy Star certification status and with the other energy-related attributes (i.e., dummies for above mean size and freezer location and indicators for each brand). Under this specification, both the magnitude of the coefficient on energy costs and the measure of energy responsiveness are quite similar to columns 2 and 3. This suggests that, conditional on our existing controls, there is little remaining correlation between local energy prices and preferences for energy-related attributes. For Specifications 2–4, we fail to reject that consumers respond similarly to a $1 change in purchase price and a $1 change in the present value of lifetime operating costs.

Fig. 4 plots the relationship between sales and the remaining variation in our variables of interest for the preferred specifications. The plot of the left displays the results of a binned scatter plot of the residual variation in sales and annual energy cost and the plot on the right displays the results of a binned scatter plot of the residual variation in sales and purchase price. Conditional on the fine-grained controls, there is a strong negative correlation across the range of the remaining variation in weekly sales and both annual energy costs and purchase price.

4.2. Robustness checks

In Table 4, we examine the sensitivity of our preferred estimates to the inclusion of controls for shifts in demand for refrigerator attributes. In column 1, we include county-by-indicator for above median purchase price-by-year fixed effects to control for longer-run county-specific shocks to demand for higher price models. This has little effect on our coefficients of interest and valuation ratio, suggesting that, conditional on our existing controls, local shocks in demand for higher price items do not significantly affect our findings.[14]

In column 2, we include Energy Star indicator-by-week, refrigerator size-by-week, and freezer location (i.e. top, bottom, or side-by-side)-by-week fixed effects. These fixed effects control for any shorter-run changes in demand for these attributes over time. In column 3, we control for zip code-by-week fixed effects, which control for local shifts in demand that could be driven by changes in the types of customers at the retailer due to substitution to other retailers. For both columns 2 and 3, the coefficient on purchase price and the valuation ratio shifts little compared to our preferred specification. This indicates that the retailer's pricing algorithm generates model-specific idiosyncratic variation that is not correlated with demand shocks.[15]

In column 4, in addition to zip code-by-week fixed effects, we include demographic-by-product fixed effects to control for the time-invariant preferences of consumers with particular demographics. The inclusion of these controls does little to change the coefficients on price and on annual energy costs. This suggests that it is the variation in electricity costs and in purchase prices that is driving our coefficient estimates, rather than correlations between the types of consumers in certain areas and product attributes such as energy costs.

In Table 5, we address measurement error in our constructed measure of local energy costs by implementing the two instrumental variable strategies described above. For our fuel price instrument, the utilities for which we constructed fuel shares using EIA form 860 did not perfectly map to all of the counties in our sample, so we perform the IV approach on an subsample of our data (about 80% of the sample). In column 1, we estimate our preferred specification (Table 3 column 4) on this subsample of data using a Poisson regression and in columns 2 and 3, we instrument for energy costs using each of the two instruments described above. Specifically, we estimate the linear first stage using OLS and then use the control function method with the non-linear Poisson regression in the second stage. In addition, we assess the robustness of the control function approach using 2SLS. In column 4, we estimate our preferred specification with OLS where the number of product j sold in county c in week t (q_{jct}) is the outcome variable. Then, in columns 5 and 6, we estimate 2SLS for each of the two instruments for energy costs.

The results in column 1 show that limiting our sample has little impact on the results from our preferred specification, indicating that the counties for which we were able to construct the fuel price instrument were representative of our full sample. In addition, the

[14] Appendix C.1 we show that the results are quite similar if we include county-by-energy-related attributes-by-year fixed effects, suggesting that changes over time in county-level preferences for these attributes are not a significant biasing factor in the analysis. For further evidence, see Appendix Table H.2 for year-specific estimates of the effects of price and energy costs on demand.

[15] Consistent with these findings, in Appendix Table G.1 we show robustness to zip code-by-week-by-above median price and zip code-by-week-by brand fixed effects.

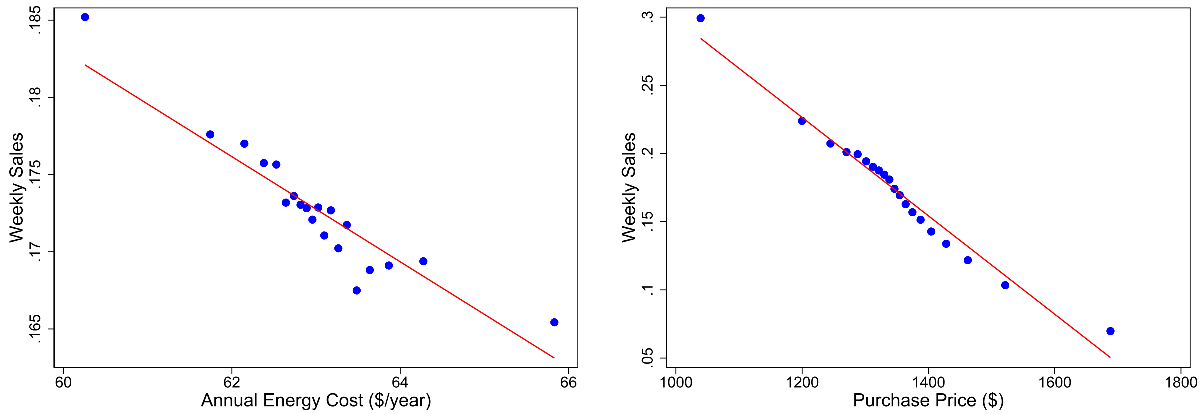

Fig. 4. Binned Scatter Plots of Weekly Sales by Annual Energy Cost ($/Year) and Purchase Price ($). *Notes:* These figures are binned scatter plots of the relationship between the residual variation in weekly sales and annual energy cost (left) and the relationship between residual variation between weekly sales and purchase price (right) in the preferred specification. Along with Annual Energy Costs and Purchase Price, the preferred specification includes controls for rebates offered for Energy Star certified products as well as county-by-year, product, brand-by-week and county-by-efficiency attribute fixed effects. Efficiency attributes include indicators for model type, above mean fridge size, Energy Star certification and each of the 10 brands in the sample. For the purposes of scaling, the mean of each variable is added back to the residuals.

Table 4
Robustness Tests.

	(1)	(2)	(3)	(4)
Purchase Price	−0.223***	−0.214***	−0.224***	−0.225***
	(0.00306)	(0.00369)	(0.00387)	(0.00380)
Annual Energy Cost	−2.123***	−2.137***	−2.081***	−2.061***
	(0.181)	(0.183)	(0.172)	(0.168)
Fixed Effects				
Product	Yes	Yes	Yes	Yes
County × Year	Yes	Yes	No	No
Brand × Week	Yes	Yes	Yes	Yes
County × Efficiency Attributes	Yes	Yes	Yes	Yes
County × Above Median Price × Year	Yes	No	No	No
Efficiency Attributes × Week	No	Yes	No	No
Zip Code × Week	No	No	Yes	Yes
Demographic × Product	No	No	No	Yes
Observations	9255983	9248783	9094339	9046790
Valuation Ratio	1.076	1.127	1.050	1.035
	(0.092)	(0.092)	(0.089)	(0.085)
Test valuation ratio = 1				
P-value	0.4084	0.1692	0.5771	0.6793

Notes: The dependent variable is the number of units of a particular appliance sold in a given week in a given zip code. The Standard errors are clustered at the county level and are in parentheses. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels. The Purchase Price and Annual Energy Cost variables are in hundreds of dollars. The valuation ratios are computed assuming a discount rate of 5% and a refrigerator lifetime of 12 years.

valuation ratio computed using OLS ($m = 1.081$) is quite similar to those using the Poisson regression ($m = 1.046$).[16]

The results from both the control function approach (column 2) and the 2SLS estimation (column 5) show that the results using the fuel price-based instrument are quite consistent with our preferred specifications. The first stage estimates in Appendix E indicate that county-level fuel prices are highly correlated with the fuel price instrument. Therefore, given the controls in our model, this suggests that the identifying energy cost variation is driven by the pre-determined electric generation fuel mix and exogenous supply side shocks to fuel prices. We also show in Appendix C that using state rather than county average electricity prices to calculate energy costs and limiting our sample to counties served by just one utility has little effect on our estimates. Consistent with the IV results, this suggests that measurement error in county-level prices is not a significant biasing factor in our analysis.

In columns 3 and 6, we instrument for electricity costs using the grouping estimator instrument as described above. The coefficient on annual energy cost is somewhat lower with this instrument and the valuation ratio is 0.74, consistent with modest undervaluation. However, the magnitude of the estimate is likely affected by the categorization of products into groups. Using just two groups is the most conservative way to characterize consumers' broad categorization of products as "efficient" or "inefficient." But, the tradeoff is that grouping in this way effectively reduces the amount of identifying variation. In Appendix F we provide evidence that this is likely driving the somewhat lower valuation ratio that we find with this instrument. The valuation ratios with instruments constructed using 3 and 4 efficiency groupings for each refrigerator type, rather than 2 are higher and no longer statistically distinguishable from one.

In Appendix G, we further probe the robustness of the identifying purchase price variation. We show that the inclusion of lagged price controls have little effect on our coefficients of interest, suggesting that price dynamics are also not an important biasing factor in the analysis. Further, we use an instrumental variables

[16] Given the difference in functional form, the OLS and Poisson coefficients are not readily comparable, though the valuation ratios are.

Table 5
Control Function and 2SLS Estimation of the Effect of Price and Energy Costs on Demand.

	(1)	(2)	(3)	(4)	(5)	(6)
Purchase Price	−0.225***	−0.225***	−0.225***	−0.0363***	−0.0363***	−0.0364***
	(0.00400)	(0.00396)	(0.00415)	(0.000807)	(0.000806)	(0.000849)
Annual Energy Cost	−2.082***	−2.415***	−1.469***	−0.347***	−0.435***	−0.302***
	(0.196)	(0.459)	(0.147)	(0.0439)	(0.0787)	(0.0358)
1st Stage Residuals (IV 1)		0.390				
		(0.566)				
1st Stage Residuals (IV 2)			−0.531***			
			(0.120)			
Fixed Effects						
Product	Yes	Yes	Yes	Yes	Yes	Yes
County × Year	Yes	Yes	Yes	Yes	Yes	Yes
Brand × Week	Yes	Yes	Yes	Yes	Yes	Yes
County × Efficiency Attributes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7310992	7310992	7310992	7395634	7395634	7395634
Valuation Ratio	1.046	1.213	0.738	1.081	1.354	0.936
	(0.096)	(0.222)	(0.0722)	(0.133)	(0.245)	(0.111)
Test valuation ratio = 1						
P-value	0.6326	0.3373	0.0003	0.5451	0.1485	0.5636

Notes: The standard errors are clustered at the county level and are in parentheses. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels. Column 3 standard errors are bootstrapped based on 200 iterations. For all estimations the sample is restricted to those observations for which we can construct the capacity-weighted fuel price instrument for energy cost. The first column is our preferred Poisson estimation. Columns 2 and 3 display the results of the second stage of control function regressions with each of two different instruments for price. Column 4 is our preferred specification estimated with OLS. Columns 5 and 6 display the results of 2SLS estimations. In columns 2 and 5, we instrument for annual energy costs using the product of the local utility's capacity-weighted fuel price and the manufacturer's reported annual kwh consumption. In columns 3 and 6 we instrument using a grouping estimator as described in the main text. The first-stage results are presented in Table E.1. The Purchase Price and Annual Energy Cost variables are in hundreds of dollars. Valuation ratios are computed assuming a 5% discount rate and refrigerator lifetime of 12 years.

Table 6
Sensitivity of Energy Cost Responsiveness Estimates to Parameter Assumptions.

	Expected Lifetime			
Discount Rate	10 Year	12 Year	15 Year	18 Year
2 percent	1.022	0.868	0.714	0.612
3 percent	1.076	0.922	0.769	0.667
4 percent	1.131	0.978	0.825	0.725
5 percent	1.188	1.035	0.884	0.785
6 percent	1.247	1.095	0.945	0.848
10 percent	1.494	1.347	1.207	1.119

approach to address any remaining endogeneity between local demand and product price. We construct an instrument for the product price at a particular location in a particular week using the average price paid that week at all other locations (excluding where the purchase was made).[17] Our results using this approach are quite consistent–we cannot reject a valuation ratio of one–suggesting that there is unlikely any significant remaining endogeneity between local demand and product price, conditional on controls.

Finally, we also do a bounding exercise, which we report in Appendix G.2, to probe the impact of substitution across local retail chains and correlation in product-specific local purchase prices. We extend the choice model to explicitly account for the choice between different local retailers and introduce correlated shocks in purchase prices across stores. Overall, this exercise reveals that using data from only one retailer could induce modest bias in m. Our simulations suggest that the magnitude of the bias could be of the order of ±0.05 of the value of m.[18]

4.3. Sensitivity analysis and heterogeneity

Table 6 shows the sensitivity of the energy cost responsiveness estimates to the assumptions we used to construct lifetime energy costs. For this analysis, we use the coefficients from our preferred estimation (column 4 in Table 3). We look at the effect of applying different discount rates ranging from 2 to 10 percent. For refrigerator lifetimes, we apply 10, 12, 15, and 18 years. Recall, for our primary estimate, we assumed a discount rate of 5% and a lifetime of 12 years, with an estimated valuation ratio of 1.035. This sensitivity analysis shows that for a wide range of expected lifetime and discount rate assumptions, we cannot reject that consumers value discounted future energy costs and purchase price similarly, as economic theory would predict. On the more extreme ends of the parameter ranges we display here, the valuation ratio estimates would suggest modest over or undervaluation of energy costs. However, our estimates clearly show that on average consumers are responsive energy operating costs, using information about local electricity prices when purchasing an appliance.[19]

[17] The advantage of this "leave-one-out" instrument is that the variation in product price is driven by idiosyncratic changes in the retailers' national pricing algorithm and not by potentially endogenous local promotions.

[18] Our bounding exercise uses a nested logit to account for correlation in idiosyncratic preferences within retail chain. We do not consider more complex correlation structure within product groups, which could also impact the bounds on m.

[19] Table 6 is also useful for thinking through the implications of systematic heterogeneity in the key parameters that enter the calculation of discounted lifetime energy costs. For example, suppose expected refrigerator lifetimes differed across the population in a systematic way, due either to usage patterns or other unobserved factors. Going from an expected lifetime of 10 to 18 years, the parameter could vary by as much as 40% for r = 2%, or 25% for r = 10%.

To better understand the drivers of consumers' attention to energy costs, we estimate valuation ratios allowing for heterogeneity along several dimensions: purchase price, consumer income, and consumer education. Specifically, we estimate a model with the same fixed effects and controls as our preferred specification, where we interact both purchase price and annual energy cost with indicator variables for each dimension of heterogeneity that we explore. Table 7 displays the coefficient estimates by each tercile of purchase price (column 1), tercile of consumer income (column 2), or level of consumer education (column 3). For education, we distinguish between secondary and professional training (level 1), college (level 2), and post-graduate education (level 3). The valuation ratio specific to each of these groupings is displayed in the bottom panel of the table with standard errors in parentheses.

In column 1, the weight consumers place on purchase price appears to vary little by the level of the purchase price. There also does not appear to be significant variation in the weight consumers place on energy costs by purchase price. The coefficient estimate for energy costs is somewhat higher for the highest tercile and somewhat lower for the lowest tercile of purchase price relative to the middle tercile. However, neither the coefficient estimates nor the valuation ratios are statistically distinguishable from one another among terciles.

In column 2, the results are more stark. Consumers in the lowest income tercile place relatively *more* weight on purchase price and relatively *less* weight on energy costs than in the middle income tercile. Conversely, consumers in the highest income tercile place relatively *more* weight on energy costs and relatively *less* weight on purchase price than the middle income tercile. The valuation ratios for the lower two terciles are not statistically distinguishable from each other or from one. However, the valuation ratio for the highest income tercile is statistically higher than for the middle and lowest terciles. Given the 95% confidence intervals, we can rule out that the valuation ratio is the same for the highest income tercile as for the other terciles.

In column 3, a similar pattern emerges with education as with income. Consumers with lower levels of education place relatively *more* weight on purchase price and relatively *less* weight on energy costs. And, consumers with the higher education place relatively *more* weight on energy costs and relatively *less* weight on purchase price. As with income, the valuation ratios for the lower two education categories are not statistically distinguishable from each other or from one. Whereas, the valuation ratio for the highest education level is statistically higher than for either of the lower two levels.

These findings are consistent with previous work documenting that time preference rates are negatively correlated with both income and education (e.g., Lawrance, 1991). The early studies on the valuation of energy costs in the context of energy-using durables also find that income and implied discount rates are negatively correlated (Hausman, 1979; Train, 1985). The coefficients on purchase price in column 2 suggest that sensitivity to capital costs vary by income in our context, perhaps due to credit constraints. Interestingly, the coefficients on annual energy costs also vary by income, conditional on purchase price. This suggests that there are inherent time preference differences across the income spectrum that could be stemming from differential access to credit or behavioral phenomena.[20]

In Appendix H, we explore heterogeneity in the purchase price and annual energy cost coefficients along three additional dimensions: (1) manufacturers' reported annual kwh consumption, (2) county electricity price and (3) year. We find that consumers place relatively more weight on energy costs and relatively less weight on purchase price as annual consumption increases. This pattern is consistent with those in Table 7, because individuals with higher income are more likely to purchase higher consumption models, which are larger and have more features. We do not find any discernible pattern in valuation of energy costs by electricity price conditional on our controls.

The yearly results show that the valuation ratio for years 2008, 2009, and 2011 are not statistically different from one. However, in 2010, the valuation ratio is lower than one, and in 2012, it is somewhat higher than one. These patterns could in part be driven by the Great Recession lowering income and constraining access to credit in 2010 and then the lower interest rates and higher income during the recovery in 2012. However, we further show in Appendix H that the results from our preferred specification when we drop observations in the year 2010 are quite consistent with those using the full sample in Table 3. Therefore, it does not appear that the presence of the Great Recession during our sample period is driving our primary results.

5. Policy implications

Our results have important implications for understanding demand response to electricity prices. Because consumers are changing their appliance choices in response to local energy prices, capital investments are an important margin to consider when designing energy and climate policies. As demonstrated by Borenstein and Bushnell (2018), in the U.S., residential electricity prices are almost always set far from their optimal social marginal costs. This is due to a variety of reasons, including that: 1) many electric utilities recover fixed costs through marginal prices, 2) negative externalities are often unaccounted for, and 3) non-linear pricing schemes are used for redistribution purposes.

Our demand model allows us to simulate induced aggregate electricity demand. We do this for two important policy scenarios that impact local electricity prices. First, we consider the effect of a national carbon pricing scheme. In particular, we increase electricity prices by an amount corresponding to a carbon externality of \$50/ton of CO2. Given that the generation mix varies widely across the U.S., we vary the size of the carbon price add-on accordingly. In the second scenario, we consider the impact of a comprehensive electricity tariff reform that sets the average variable charge equal to the optimal social marginal cost.

To perform the analysis, we borrow Borenstein and Bushnell (2018)'s constructed measures of local average electricity prices, social marginal prices, carbon price add-ons, and private marginal prices for the period 2014–2018. To estimate baseline demand, we simulate our estimated demand model with their local average electricity prices.[21] We compute induced energy demand by multiplying the model-specific sales predictions from our model by the corresponding annual energy consumption (as reported by the manufacturer).

We then re-simulate the demand model for each of the two policy scenarios. In the first scenario, we incorporate a carbon price add-on specific to the local generation mix to each county's baseline average price. In the second scenario, we use the county-level average social marginal price instead of the average price. Finally, to investigate the sensitivity of the results to our parameter estimates, we consider the lower and upper bound of the 95% con-

[20] In Appendix Table C.4, we test whether there is heterogeneity stemming from promotional pricing or subsidies. For sub-samples of regions and times where promotions and subsidies are not available, the results are quite consistent with the full sample. This suggests that the prevalence of sales or subsidies are not driving the finding that consumers are attentive to local energy costs.

[21] To obtain internally consistent policy scenarios, we use Borenstein and Bushnell (2018)'s electricity price data from more recent years than our sample period for our policy simulation. Specifically, the local average electricity price is the county average over the period 2014–2018.

Table 7
Heterogeneity in the Effects of Price and Energy Costs on Demand.

	(1)	(2)	(3)
Purchase Price Tercile 1 × Purchase Price	−0.222***		
	(0.00911)		
Purchase Price Tercile 2 × Purchase Price	−0.223***		
	(0.00569)		
Purchase Price Tercile 3 × Purchase Price	−0.221***		
	(0.00224)		
Purchase Price Tercile 1 × Annual Energy Cost	−1.904***		
	(0.176)		
Purchase Price Tercile 2 × Annual Energy Cost	−2.089***		
	(0.176)		
Purchase Price Tercile 3 × Annual Energy Cost	−2.138***		
	(0.196)		
Income Tercile 1 × Purchase Price		−0.231***	
		(0.00339)	
Income Tercile 2 × Purchase Price		−0.219***	
		(0.00304)	
Income Tercile 3 × Purchase Price		−0.209***	
		(0.00340)	
Income Tercile 1 × Annual Energy Cost		−1.979***	
		(0.170)	
Income Tercile 2 × Annual Energy Cost		−2.197***	
		(0.175)	
Income Tercile 3 × Annual Energy Cost		−2.505***	
		(0.177)	
Education Level 1 × Purchase Price			−0.228***
			(0.00349)
Education Level 2 × Purchase Price			−0.224***
			(0.00323)
Education Level 3 × Purchase Price			−0.221***
			(0.00336)
Education Level 1 × Annual Energy Cost			−2.061***
			(0.178)
Education Level 2 × Annual Energy Cost			−2.085***
			(0.176)
Education Level 3 × Annual Energy Cost			−2.571***
			(0.192)
Fixed Effects			
Product	Yes	Yes	Yes
County × Year	Yes	Yes	Yes
Brand × Week	Yes	Yes	Yes
County × Efficiency Attributes	Yes	Yes	Yes
Observations	9255983	9236743	9229721
Valuation Ratio			
Category 1	0.966	0.967	1.018
	(0.105)	(0.081)	(0.087)
Category 2	1.056	1.131	1.049
	(0.093)	(0.088)	(0.087)
Category 3	1.091	1.349	1.314
	(0.097)	(0.094)	(0.099)

Notes: Each model is estimated using a Poisson regression. The dependent variable is the number of units of a particular refrigerator model sold in a given week in a given zip code. The standard errors are clustered at the county level and are in parentheses. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels. The Purchase Price and Annual Energy Cost variables are in hundreds of dollars. The valuation ratios are computed assuming a discount rate of 5% and a refrigerator lifetime of 12 years. Education category 1 refers to secondary and professional training, category 2 refers to college and category 3 refers to post-graduate education.

fidence interval of our preferred estimate of the valuation ratio (column 4 of Table 3).

Table 8 presents the results of these simulations relative to the baseline scenario. Column I shows the effect of a carbon price add-on and Column II shows the impact of switching to social marginal cost. The first row reports the average percentage change in price that each policy produces across the zip codes served by the retailer. A carbon externality of \$50/ton of CO2 translates into a 19% price increase.[22] Interestingly, the switch from average pricing to social marginal pricing leads to an average *reduction* of almost 25% in price for the region served by the retailer. As discussed by Borenstein and Bushnell (2018), this result is surprising but has a simple explanation. Given that electric utilities often pass their fixed costs on to consumers by charging higher marginal prices, electricity tariffs are actually higher than the optimal social marginal price in large regions of the U.S.

The impact on expected induced energy demand is shown on the second row. The carbon price add-on reduces demand by about 24%. To put this number in perspective, during the sample period Energy Star-certified refrigerators had to be 20% more efficient than refrigerators that just met the federal minimum standards. The impact of carbon pricing on electricity demand is thus large and comparable to Energy Star—the main policy that is currently in place in the U.S. to favor the adoption of more energy-efficient appliances.

The impact of switching to social marginal prices is even larger but leads to an increase in induced electricity demand. This sug-

[22] This average is not sales weighted, but considers only counties for which we simulate sales, i.e., where our retailer has at least one appliance store.

Table 8
Policy Analysis.

	Scenario I Average Price + CO2 Tax	Scenario II Full Social Marginal Price
Change in Price (%)	19.2	−24.7
Change in E[kWh/y] (%)	−23.9	41.5
	[−20.3, −27.3]	[33.5, 50.0]
Elasticity	−1.3	−1.7
	[−1.1, −1.5]	[−1.4, −2.1]
Total Change in GWh/y	−356.9	1158.6
	[−317.9, −391.5]	[1085.3, 1208.8]

Notes: For both scenarios, the estimates represent changes relative to the baseline scenario where electricity prices are equal to the county-level average electricity prices. All electricity prices are from Borenstein and Bushnell (2018). The demand model is simulated using the estimates from Specification 4 in Table 3. The number in brackets corresponds to the demand model simulated with the lower and upper bound of the 95% confidence interval for the parameter on electricity costs.

gests that existing rate distortions are of first order importance in considering the effects of climate policy on appliance demand. The substantial rate increases we find for carbon policy can exacerbate existing distortions. If we translate the demand changes we estimate into elasticity, we have elasticities of −1.3 and −1.7 for the first and second scenario, respectively. In the Appendix (Table I.1) we examine why these elasticities are different. We show that a decrease in electricity prices has a greater proportional impact on induced electricity demand than an equivalent increase in prices. The intuition behind this result is that a decrease in energy operating costs makes cheaper and less efficient models disproportionately more affordable, which drives the elasticity up.

In the Appendix (Table I.1), we also show the impact of alternative, smaller or larger, carbon price add-ons. We find that the level of the response is approximately proportional. This suggests that the elasticity of −1.3 found in Table 8 for the first scenario is thus useful to simulate alternative scenarios with respect to an impact of a carbon price add-on.

The last row of Table 8 shows the overall change in electricity demand induced by each policy. However, this number should be interpreted with a number of caveats. First, our demand model is estimated for only one appliance category: refrigerators. These policies would also impact demand for other large appliances and consumer electronics. Second, we estimate the demand model on single-family households only, which is a subset of the overall demand for large appliances. Contractors, renters, or owners of large apartment buildings might all respond differently to local electricity prices. Third, we simulate total sales for only one retailer. During that period, our retailer's national market shares were about 30% of the U.S. appliance market. Therefore, if our retailer is representative of the rest of appliance sales, a national estimate would be 3 to 4 times larger than what is presented here.

Our policy analysis focuses on interventions that change local electricity prices. In the policy debate about managing energy demand, non-price interventions are also often discussed. Investment inefficiencies due to various behavioral phenomena are often a rationale for policy interventions. Our results suggest that, on average, consumers' degree of responsiveness does not lead to a large under- or over-valuation of appliances' energy costs. Heterogeneity ought to be important, however. Table 7 shows that income, among other dimensions, plays a role, where high-income consumers respond more to energy costs relative to low-income consumers. We explore the energy consumption impact of a non-price intervention resulting in all consumers having preferences aligned with those of either the highest or lowest income tercile and compare the magnitude of such interventions with those from a carbon tax add-on or a redesign of the electricity tariffs in line with social cost pricing. In Table I.2 in Appendix I, we show that the impact of increasing the energy cost responsiveness of the lower income terciles to that of the highest tercile is in line with a large carbon tax—a $75/ton of CO2 add-on. If we decrease the energy cost responsiveness of the higher income terciles to that of the lowest tercile, energy consumption goes up, but not nearly to the degree that it would if retail rates were changed to reflect social cost pricing. The magnitudes of these impacts suggest that carefully designed and targeted non-price interventions could potentially complement pricing interventions.

6. Conclusion

Consumer responsiveness to local electricity prices is a critical input for a myriad of energy and pollution policies that impact residential electricity markets. This paper explores how responsive consumers (primarily homeowners) are to energy operating costs. Compared to other contexts, such as gasoline costs for driving, it is not straightforward for households to quantify the operating costs of appliance usage, since they are billed on a monthly basis for all combined uses of electricity. Given the importance of appliance purchasing behavior for energy and pollution policy, consumer responsiveness to energy costs in appliance markets is relatively understudied, largely due to limited availability of micro data.

In this paper, we exploit a unique administrative data set from an appliance retailer, with individual transaction data tracking the price and location for each model sold. We compare the demand response from changes in the potentially misperceived energy costs to the demand response from changes in correctly perceived product prices. We estimate responsiveness to product price using exogenous variation created by the retailer's national pricing algorithm, which results in large and frequent model-specific price changes. We estimate responsiveness to energy costs using the relative differences in operating costs between more and less efficient models, which varies with electricity prices across space and time. We control for county-by-time specific movements in appliance demand to isolate the effect energy operating costs from confounding market conditions, which might affect the probability of buying an appliance at all.

We find strong evidence that homeowners are responsive to local energy operating costs. The results from our preferred specification suggest that consumers are close to indifferent between $1.00 in discount future energy costs, at a 5% discount rate, and $1.00 in purchase price. We find that, while consumer income is somewhat negatively correlated with valuation of lifetime energy, consumers across the income spectrum appear fully attentive to energy costs. Our policy simulations suggest that, because consumers do respond to local energy costs, existing rate deviations from optimal social marginal costs have large distortionary effects on demand and important implications for carbon pricing policies, which may exacerbate these distortions.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jpubeco.2021.104480.

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