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The Impact of Energy Prices on Energy Efficiency: Evidence from the UK Refrigerator Market[1]

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Abstract

It is commonly believed that large energy efficiency gaps exist in the energy-using durables markets. We develop a broad analytical framework capturing consumer purchase behavior and suppliers' pricing and innovation decisions to estimate the effect of household electricity price variations on the refrigerator market outcomes. Using UK product-level panel data from 2002 to 2007, we find that the main factor limiting the full effect of rising price signals on curbing energy consumption of refrigerators is not consumer myopia, but changes in relative prices of products in favor of the less efficient models. We also find that manufacturers strongly respond to rising electricity prices by changing their product

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portfolio. This suggests shifting policy attention towards suppliers' pricing and innovation behaviors would be effective in achieving energy efficiency gains in the durables market.

Keywords: Energy Efficiency; Electricity Prices; Consumer Myopia, Imperfect Competition.

JEL Classification: D12, L68, Q41.

1. Introduction

In energy and environmental policy circles, the promotion of energy efficiency is viewed as a major objective because of its relation to energy security, environmental objectives including CO_2 mitigation, job creation and other economic benefits. This has led to continued developments of policies for energy conservation, including labeling schemes, binding standard and price incentives. This applies particularly to the commercial and residential sectors where it is widely believed that significant "energy efficiency gaps" exist between the socially optimal and actual level of energy consumption. The International Energy Agency has been particularly active in disseminating this idea (see for instance, IEA, 2007, Ryan et al., 2011).

Energy efficiency outcomes involve decisions where consumers first make an upfront investment in a durable good and then consume the energy that is required to use the product. Examples include water heaters, insulation in buildings, motor vehicles and household appliances. Efficiently functioning markets for energy-using durables is thus a key ingredient. The idea of the energy efficiency gap is rooted in the widespread belief that the markets of energy-using durables fail to properly integrate energy price signals. The policy discussions, as well as the academic literature, mostly focus on demand-side issues (see IEA, 2007, Ryan et al., 2011 and the reviews by Allcott and Greenstone, 2012, and Gillinghan and Palmer, 2014). The key concern here is that imperfect information and other cognitive constraints could lead consumers to discard privately profitable investments[2]. Since the seminal paper by Hausman (1979), it is often asserted that consumers are myopic in the sense that they give too high weight to the upfront cost or, expressed differently, the implicit discount rate used to calculate the net present value of the investment is too high. In contrast, much less attention has been paid to the supply side of these markets[3].

In this paper, we develop a broad analytical framework that includes both consumer and supplier behaviors to identify how refrigerator markets respond to energy prices. On the demand side, an increase in electricity price reduces consumer utility. As the reduction is higher for energy-inefficient products, it provides incentives to shift towards more efficient ones. On the supply side, the durables producers then adjust prices in response to this demand shock. The theory of industrial organization predicts an asymmetric response in differentiated good markets: the price of models with poor energy performance is expected to decrease, while that of energy-efficient models will decrease less or even increase if total demand is sufficiently inelastic. Note that this price adjustment would not occur in a competitive market where prices are equal to marginal production costs, because there is no

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[2] The nature of the underlying causes of demand inefficiencies is extensively discussed by Gillingham and Palmer (2014). Most of these causes are related to imperfect information. The simplest mechanism is when the decision maker lacks information on the true benefits of energy efficiency investments. But there can also be principal-agent problems arising when one party makes a decision related to energy use, but another party pays or benefits from that decision. For example, the landlord may pay for heating, while the tenant chooses how much energy to use. Another potential barrier is if the investor faces credit constraints that are stronger than for other investments because the lender finds it difficult to evaluate the payoff from energy efficiency investments.

[3] The academic literature is reviewed in the subsequent section. Supply side aspects have been studied for instance by Fischer (2005), Jacobsen (2013), Houde (2014a, 2014b), Goldberg (1998). In contrast with our paper, most of these papers do not investigate the impact of energy prices, but that of other policy instruments (e.g. standards and energy labelling).

price change if marginal costs are constant.[4] Producers can also modify their product portfolio by launching new energy efficient models and withdrawing inefficient ones.

We use annual product-level panel data from the U.K. refrigerator market from 2002 to 2007 to analyze the entire sequence of adjustments and their impact on energy use of sold appliances. We incorporate three relevant market dimensions: consumer behavior, suppliers' price setting behavior and suppliers' product innovation behavior. Using data on sales, prices and the set of products sold in the market in a given year, the variation in the price of electricity over time and the product-specific variations in energy consumption levels are exploited to identify the impact of changes in electricity price on the different dimensions.

In doing so, we examine the previously neglected potential role of suppliers in widening the "energy efficiency gap". In particular, the potential change in relative prices between energy efficient and inefficient goods means that producers subsidize inefficient models in relative terms. The implication is that like consumer myopia, the effect of rising energy prices on energy efficiency is weakened as incentives to shift to efficient models are dampened. We also look at their role in narrowing the energy efficiency gap when they change product characteristics, which can boost the impact of energy price on average energy performance of sold appliances. A full understanding of the impact of energy prices on energy use thus requires taking all these decisions into account.[5]

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[4] Constant marginal cost is a reasonable assumption as our scenario does modify the quantities produced drastically.

[5] This point is also made with an analytical model by Fischer (2005) who stresses the importance of the supply side factors (including innovation) when designing policies to promote energy efficiency of household appliances.

Methodologically, we develop a simple discrete choice model with differentiated quality based on Berry (1994) to describe demand. We take the first-difference to eliminate time-invariant product attributes. A nested logit framework is used to control for product segmentation caused by product differentiation. To address endogeneity issues arising from refrigerators' prices and quantities being simultaneously determined, our instrumentation strategy incorporates data from product markets with different demand characteristics that are sold and manufactured by the same firms supplying refrigerators. Adjustments made by suppliers to prices and products offered are estimated using reduced-form equations, which impose few restrictions on how they compete on the market. To estimate how electricity prices influence which products are offered on the market, we use a dynamic panel-data probit model (Wooldridge 2005), taking advantage of the fact that for a given model, the dates of market entry and exit are observed. We then use our estimates to simulate the impact of an increase in electricity price on the average annual electricity consumption of sold appliances. The simulations include three stages: first, we predict the impact of electricity price shocks on purchasing decisions, holding the set of products available on the market and their prices constant. Second, we predict how an electricity price rise affects relative refrigerator purchase prices and adjust market shares accordingly. Third, we correct the market shares of commercialized products according to their probability of being commercialized, which we estimate with a probit model.

What transpires from our estimates is the fact that the refrigerator market strongly responds to electricity price changes. On the demand side, our base specification predicts that, holding the supply behaviour constant, a 10% electricity price increase is associated with a reduction in energy use by 2.1%. This reflects limited consumer myopia as our estimate of the implied discount rate is 11%. Multiple robustness checks confirm this finding.

In the second stage where product characteristics are held constant, we find suppliers' decisions to cut prices of inefficient durables drastically reduce the impact of rising electricity price on energy use – energy use reduction falls to 0.5%. The reason is that adjustments to refrigerator prices are large, compensating around 75% of the increase in lifetime energy costs. In the third stage, the innovation response is also drastic as endogenous changes in product characteristics double the size of energy use reductions – it increases to 1.0%.

What policy lessons can be drawn from these figures? The potential existence of inefficiencies in the markets of energy-using durables has important policy implications (Allcott and Greenstone, 2012; Gillingham and Palmer, 2014; Jaffe and Stavins, 1994; Verboven, 2002, Li et al., 2009). Policies designed to improve the energy efficiency of durables reflect the conventional view that price instruments such as emissions trading are likely to have limited impacts on residential energy use, because households underestimate the size of future energy costs. These include investment subsidies that encourage the purchase of water heaters, the installation of insulation in dwellings, regulatory standards mandating a minimal level of energy or environmental performances of new motor vehicles like the EURO norms in Europe or the CAFE standards in the U.S., building energy codes and product energy labels.

Our findings partly contradict this view. The problem is not the lack of consumer response to energy price rises in their durables consumption behavior per se. Rather, the major source of inefficiency results from a very strong response by suppliers in adjusting product prices, specifically by reducing the relative price of energy inefficient models. Thus focusing solely on the demand side issues is unlikely to lead to a comprehensive set of policies to tackle the energy efficiency gap. For example, energy labelling can constitute a partial solution to demand-side failures, but it does not mitigate the pricing problem. It can even be counterproductive and exacerbate the problem by providing producers with more incentive to subsidize inefficient models if consumers respond to labeling. Our finding that the innovation response to energy prices is relatively large, also contradicts a popular idea in policy circles that energy performance standards are the preferred tool to force inefficient models to exit the market. To sum, supply-side issues should be at the core of the policy discussions on energy efficiency.

The rest of this paper is structured as follows. In the following section, we briefly review the literature and justify why refrigerators constitute a suitable case study to investigate the functioning of durable goods markets. Section 3 develops a conceptual framework and address identification issues. Section 4 presents the data. Sections 5 outlines our empirical strategy and estimated results are presented in Section 6. In Section 7, we run simulations to predict the impacts of a 10% increase of the price of electricity. Section 8 summarizes our findings and formulates policy implications.

2. Related literature

The empirical literature on the impact of energy prices on energy efficiency is well developed. However, to the best of our knowledge, there exists no work which studies the impact of energy price changes on the entire sequence of demand and supply responses (quantity, price, and innovation).

As explained above, the large majority of existing papers focus on demand and consumer myopia. Following the work of Hausman (1979) on room air conditioners, earlier research found implicit discount rates that are substantially larger than real financial discount rates. In the case of electric appliances, rates reported for refrigerators range from 39% to 300%

(Revelt and Train, 1998; Hwang et al., 1994; McRae, 1985; Meier and Whittier, 1983; Gately, 1980; Cole and Fuller, 1980); between 19% to 77% for air conditioners (Matsumoto, 2012; Train and Atherton, 1995; Hausman, 1979; Kooreman, 1995); and between 67% and 84% for water heaters (Hwang et al., 1994; Goett and McFadden, 1982). More recent studies have suggested lower rates. For refrigerators, Tsvetanov and Segerson (2014) find discount rates in the range 13-22% in a paper that looks at the impact on consumer surplus of energy labeling. The same pattern is found in recent papers dealing with gasoline prices and fuel efficiency. Allcott and Wozny (2014), whose methodological approach is similar to ours, find a discount rate of 16%. Busse et al. (2013) produce several estimates under different assumptions, none of which exceed 20% and many of which are close to zero. The same pattern is found by Goldberg (1998).

There are several reasons which explain why recent works, including ours, find low discount rates compared to previous work, the most important one being the use of panel data that allows unobserved product characteristics to be better controlled for. Indeed, using a hedonic pricing model on a cross section of products as done by Hausman (1979), we find a discount rate of 210% (see Annex A5). Another reason may also be related to the fact that consumers are better informed. For example, energy labelling is mandatory in the European Union for many appliances, including refrigerators, since 1995. In the US and in Canada, the label “Energy Star” is also increasingly used.

A few papers look both at price and quantity adjustments. Many of them investigate the impact of other policy variables, in particular energy or fuel efficiency standards (Goldberg, 1998; Jacobsen, 2013), feebates (e.g., d’Hautfeuille et al., 2013) and energy labelling (Houde, 2014a, 2014b). Two contributions deal with energy prices. Busse’s et al. (2013) work on the car market examines both the level of the discount rate and the price response of car suppliers (manufacturers and retailers) to gasoline price changes. Interestingly, they show that the price adjustment is much higher in the used car market than in the market for new cars. Verboven (2002) is primarily concerned with the pricing behavior of car manufacturers. Finally, there is a literature focusing on the impact of energy prices on innovation. Examples include the work by Newell et al. (1999) on energy-using consumer durables and by Popp (2002) on a larger set of 22 energy-related technologies.

Why is it then useful to combine the study of all adjustments as we do in this paper? The answer is very simple: it allows the assessment of the relative importance of all the issues that have been identified in the theoretical literature as relevant. Our results show that the norm of focusing on demand and consumer myopia is too restrictive to get a full understanding on how energy prices influence energy use and the policy solutions that can be introduced to complement energy taxation.

Refrigerators constitute a suitable case to explore these questions for reasons that can be better explained by a comparison with motor vehicles, where the impact of gasoline prices have been studied in several recent studies (e.g., Allcott and Wozny, 2014; Busse et al., 2013, Anderson et al., 2013). To start with, and in contrast to car owners who vary their usage intensity, refrigerator owners cannot adjust energy consumption after purchase.[6] As a result, future energy consumption is exogenously determined by the characteristics of the product. This suppresses an important source of biases and of measurement errors. A second advantage is that there is no market for used cold appliances. This is obviously not the case for cars and empirical analysis therefore needs to develop complex solutions and/or

[6] A consequence is that there is no "rebound effect", unless consumers keep their old refrigerator as a second appliance. This is unlikely in British dwellings where space is limited. The work by Sallee, West, and Fan (2009) is an example of effective efforts to circumvent that problem with controls for odometer readings.

make several assumptions to deal with this issue. See for instance Jacobsen (2013), Li et al. (2009), or Allcott and Wozny (2014) who only examine the impact of gasoline prices on the second-hand market. Third, the product is simple compared to cars and less influenced by subjective feelings. This is a major benefit as dealing with taste shocks and unobserved product characteristics, that tend to be correlated with energy performance, is a major methodological obstacle, particularly when using market level data as is done in this paper and many others. Recall also that energy labelling is mandatory since 1995 for all refrigerators sold in the European Union, meaning that information asymmetry on energy performance is to a large extent mitigated.

3. Conceptual framework

We begin by developing a simple discrete choice demand model of the refrigerator market based on Berry (1994). There are *T* markets, each representing the UK refrigerator market during year t (with t = 1,…,*T*). For each market, we observe aggregate quantities sold, average prices, and product characteristics for *J* models of refrigerators.

Consumers choose the product that maximizes utility. The indirect utility function of consumer *i* purchasing a new refrigerator *j* in year t is equal to $U_{ijt} = V_{jt} + \epsilon_{ijt}$ where V_{jt} is the average utility and ϵ_{ijt} is consumer *i*'s unobserved heterogeneity that captures deviation from the average. The average utility is:[7]

$$V_{jt} = u_{jt} - \alpha\left(p_{jt} + \gamma C_{jt}\right)$$

[7] This form of the indirect utility can be derived from a quasi-linear utility function, which is free of wealth effects. This is a reasonable assumption for refrigerators, which usually represents a tiny share of individual income.

In this expression, u_{jt} captures the value of usage of the refrigerator *j* over its lifetime which depends on product characteristics such as size, whether the refrigerator is built-in or freestanding. p_{jt} is the purchase price and C_{jt} is the discounted electricity cost. C_{jt} has a negative impact on V_{jt} which is proportional to α, the marginal utility of money, and a parameter γ, which captures consumers' perceptions about energy costs. If consumers are perfectly rational, we have $\gamma = 1$. If they are myopic, it is expected that they underestimate the disutility from energy costs so that $\gamma < 1$. Estimating this parameter is a central objective of the paper.[8]

Next we decompose the value of usage in two additively separable terms: $u_{jt} = u_j + \xi_{jt}$ where ξ_{jt} captures the time-varying component of the valuation of observed and unobserved product characteristics. Hence, we have:

$$V_{jt} = u_j - \alpha\left(p_{jt} + \gamma C_{jt}\right) + \xi_{jt}$$

Berry (1994) generalises McFadden's (1973) discrete-choice demand model by transforming the logit model into a linear model that can be estimated with aggregated market data. In Berry's framework, the probability that good *j* is purchased asymptotically corresponds to its market share at time *t*. Hence:

$$s_{jt} \equiv \frac{e^{V_{jt}}}{\sum_k e^{V_{kt}}},$$

where s_{jt} denotes product *j*'s market share in year *t.* A consumer can also choose the outside option, indexed 0, which represents the decision not to purchase any refrigerator. Normalizing the utility of the outside option V_{i0t} to zero, the market share of product *j* at

[8] Here, the modeling strategy is to adopt the standard rational choice model, except that we include the parameter γ. An alternative approach would be to adopt a behavioral economics framework, which is used by Segerson and Tsvetanov (2014). But this will prevent the measurement of the energy efficiency gap, which is precisely the gap between actual behavior and perfect rationality.

time t can be compared with the market share of the outside good so that $s_{jt}/s_{0t} = e^{V_{jt}}$. In logs, this simplifies to $\ln(s_{jt}) - \ln(s_{0t}) = V_{jt}$. This expression rests on the assumption of irrelevance of independent alternatives (IIA) that leads to biased estimates in heterogeneous, segmented product markets.

To relax this assumption, we adopt a nested logit framework in which consumers' idiosyncratic preferences are correlated across refrigerators within the same "nest" ($Corr(\epsilon_{ijt}, \epsilon_{ikt}) \neq 0$), and zero otherwise.[9] In this situation, Berry shows that:

$$\ln(s_{jt}) = u_j - \alpha(p_{jt} + \gamma C_{jt}) + \sigma \ln(s_{j(g)t}) + \ln(s_{0t}) + \xi_{jt} \tag{1}$$

where $s_{j(g)t}$ is the market share of product j as a fraction of the total sales within group g that includes product j and $\sigma \in [0,1]$ is a scalar that parameterizes the within-nest correlations. Note that the model collapses to the standard logit when $\sigma = 0$.

In our base specification, we construct the product groups based on three dimensions that create product segmentation in the refrigerator market: a capacity indicator that takes the value 1 when the capacity is above the sample median capacity; an indicator that takes the value 1 when the appliance is a combined refrigerator-freezer rather than a standard refrigerator; and an indicator that distinguishes freestanding appliances from built-in ones. This choice is based on our belief that these three characteristics naturally divide the products in different segments. A consumer purchasing a combined refrigerator-freezer has a fundamentally different need than a consumer purchasing a standard refrigerator. Similarly, the choice of the size is strongly influenced by family characteristics (size, food

[9] Goldberg (1995) and Allcott and Wozny (2014) are other examples where the nested logit model is used. A popular alternative is the random coefficient models. In this situation, the nested logit model is suitable since it allows us to eliminate unobserved quality and cost characteristics and the outside option through first-differencing. A random coefficient approach requires us to quantify the outside option, which is uncertain and subject to measurement errors.

consumption habits, etc.) and dwelling characteristics, whereas built-in refrigerators are more likely to be chosen by consumers that refurbish their kitchen at the same time. In Appendix A1, we give results with alternative nest structures which were not qualitatively affected by different nests.

We now turn to the specification of the discounted lifetime electricity cost C_{jt}, which is our variable of interest. The parameter γ is inserted in Eq. (1) to capture potential behavioral failures. As a consequence, C_{jt} should not be viewed as the electricity cost perceived by real-world consumers, but rather the cost they would consider if they were fully informed and rational. They would then calculate the net present value of the electricity cost with the standard formula:

$$C_{jt} = \Gamma_j \times \sum_{s=1}^{L_j} \frac{q_{t+s}^{f}}{(1+r)^s} \quad (2)$$

In this equation, L_j is product *j*'s lifetime, Γ_j is the level of energy consumption per time period, q_{t+s}^{f} is the electricity price at time $t+s$ that is forecasted at the time of purchase t and r is the discount rate. As we consider the behavior of a representative consumer, q_{t+s}^{f} which is a national average although actual prices can vary across locations. As a result, the variation in the data comes from the interaction between model-specific and time-invariant characteristics (i.e. lifetime and annual energy consumption) and time-varying electricity prices. Note also that forecasted electricity prices are unobserved as the data only include *actual* prices. They are estimated with an ARIMA model that is described more fully in Section 4. We come back to these issues in detail below.

Price. In contrast to the demand equation, we rely on a reduced form equation to describe refrigerator price adjustments induced by electricity price changes. Developing a structural approach to describe the supply would require taking into account both pricing and product innovation behaviour of multiproduct firms. We would thus need to introduce multiple assumptions on how competition works. Reduced form equations impose much less restrictions. Recall that our interest is in the influence of electricity costs. Accordingly, our price equation is:[10]

$$p_{j,t} = \beta - \eta C_{jt} + \mu_j + \lambda_{b(j)t} + \epsilon_{jt} \tag{3}$$

μ_j is a product fixed effect, $\lambda_{b(j)t}$ is a by brand by year fixed effects where $b(j)$ indicates the brand of product *j*. Therefore, $\lambda_{b(j)t}$ captures average shifts in the price of products from the same brand. We come back to this in Section 5 when dealing with identification issues. Our objective here is to estimate η. Importantly, this parameter measures neither the demand nor the supply curve characteristics. Instead it estimates the impact of electricity costs on the equilibrium refrigerator price, once demand and supply responses are both taken into account, holding product availability constant. Thus, this estimate allows us to derive a mid-term elasticity after quantity and price adjustments.

Product availability. Turning next to changes in product portfolio, we take advantage of the fact that data describes products sold in the market in year *t* on the product code level. Thus, we observe when specific products have been launched and when they have been withdrawn.[11] Again we expect that an increase in electricity price would induce the launch of more energy-efficient models and the withdrawal of less efficient ones.

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[10] In a variant, we include both the electricity cost and its squared value to test for the existence of a non-monotonic relationship between product price and electricity costs. It is possible that energy price increases will decrease the price of the products consuming more energy while the price of energy-efficient models could increase if total demand is inelastic. We find no support for this hypothesis; results are presented in Appendix A6.

[11] The dataset also includes products that are observed every year. That is, products that have been launched before 2002 and not been withdrawn during the sample period.

Let d_{jt}^* denote a binary variable indicating the availability of product j at time t. More specifically, $d_{jt}^* = 1$ if the product is in the market and zero otherwise. In addition, we define $d_{j,t}$ as the probability that product j is available at time t. We then use a dynamic probit equation which relates this probability to a set of explanatory variables:

$$d_{jt} = \Phi(k_d d_{jt-1}^* + k_p p_{jt} + k_c C_{jt} + \tau_t + \mu_j) \tag{4}$$

$\Phi(.)$ is a cumulative normal function with zero mean and a variance equal to one and k_d, k_p and k_c are parameters. The two crucial variables are the purchase price p_{jt} and the operating cost C_{jt}, which are both expected to decrease the dependent variable ($k_p, k_c < 0$). We adopt a dynamic specification with d_{jt-1}^* as an independent variable in order to control for path dependency: launching a product in the market is more costly than withdrawing it. τ_t and μ_j are time dummies and product fixed effects, respectively.

4. Data

We use market data from the refrigerator market in the UK on the product level from 2002 to 2007 collected by the market research company *GfK Retail and Technology* (received by the Department for Environment, Food and Rural Affairs). When investigating the influence of energy prices, a potential difficulty is that other policies such as energy labelling, feebates and energy standards may also have an impact on energy efficiency. Our study period has seen neither change in the design of the labelling scheme, nor in the strictness of regulatory standards.

However, the Energy Efficiency Commitment (EEC) scheme was enforced during the study period, offering the possibility for eligible households to get financial support for the purchase of energy efficient cold appliances, among other types of energy efficiency investments. In practice though, support provided through EEC focused on energy efficient light bulbs and on home insulation. Lees (2008) report that subsidized fridge-freezers by EEC may have represented 0.43% of the market between 2005 and 2008. If we also include subsidies from local authorities and the Warm Front, subsidized appliances may have represented around 1.5% of all cold appliances sold between 2005 and 2008. Therefore, such policies alone are unlikely to explain either consumer behavior or suppliers' reactions in general.

The data includes detailed annual information on refrigerators and combined refrigerators-freezers sold in the U.K. We identify products by brand name and series numbers. If not available, we rely on available information on product features (width, height, total capacity, energy consumption, energy efficiency rating, freestanding / built-in feature, availability of no-frost system and of freezer).[12]

Each observation is a product *j* in year *t* with measures including number of units sold, average consumer price, and annual electricity consumption. We also observe a set of product features such as size, whether it is a standard refrigerator or a combined refrigerator-freezer and indication of whether it has a separate freezing compartment that can store food at -18°C. We do not have information on product-specific lifetimes. Instead, we use the information provided by the Association of Manufacturers of Domestic Appliances that estimates the lifetime to 12.8 years for refrigerators and to 17.5 years for combined refrigerators-freezers (AMDEA, 2008).

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[12] Brand name and series numbers were not available for retailers' own brands. For these products, identification is based on product features alone. This means that, with this method, two models from different retailers' brand but with exactly the same product features cannot be properly distinguished. Therefore, observations for retailers' brand appliances are dropped each time the same product features corresponds to various models of appliances for the same year.

We drop observations with low sales. More specifically, we drop each model of which annual sales never exceeds 100 units over the study period. This ensures that the models in the sample were actually commercialized at a large scale (not only in a few local markets) during at least one year over the period. We also drop every observation (product x year) with less than 10 units sold to avoid having models with sales near zero that would make the estimation of the discrete choice model unstable. Outliers are also dropped: we identify the 2.5% products with either largest or smallest price, capacity or energy consumption, in addition to the 2.5% of products with highest sales levels. Any product following within at least one of these categories is dropped from the sample.[13]

Summary statistics on product characteristics are displayed in Table 1. The data set used in the regressions includes 3,519 observations of which 2,265 are used to construct the first differences for the econometric estimation. The total number of differences used in the econometric estimation is 1,365. Descriptive statistics are based on the 2,265 observations used to construct the differences of the estimation sample of the market share and price equations.

Although the data is not used in our estimation, we also know the product's classification according to the EU energy label. Energy labeling is mandatory since 1995 for all refrigerators sold in the European Union. In our data, each product is assigned to a class from A++ (the most energy-efficient) to G (the least energy efficient). This rating does not capture the absolute energy consumption of the appliance, but its relative consumption

[13] For the dynamic panel data probit model, we do not drop the 2.5% of products with highest or lowest price, since this would affect the normality of the price variable, and therefore undermines the multiple imputation process.

across different classes. Table 2 provides an overview of the distribution of prices and market shares across energy efficiency classes.

Table 1: Summary statistics on product characteristics

Variable	Unit	Mean	Std deviation
Annual sales, used for the log of market shares $\ln(s_{j,t})$	# of units	1371.5	2251.6
Purchase price, $p_{j,t}$	real £	394	246.7
Appliance lifetime, L_j	years	15.2	
Energy consumption, Γ_j	kWh/year	306.3	136.5
Height	cm	139.8	42.8
Width	cm	59.3	9
Capacity	litres	246.9	106.5
Energy efficiency rating[a]		2.4	0.8
Share of combined refrigerators-freezers		0.51	
Share of built-in appliances		0.74	
Share of appliances with no-frost system		0.23	

Notes. Source: GfK, provided by Defra. Survey years: 2002-2007. 2,265 observations. [a] To obtain a numeric value for the energy efficiency rating (from "G" to "A++"), ratings were recoded with "A++" set equal to 0, "A+"=1, "A"=2 and so on up to "E"=6. The data used in the regression does not comprise "F" and "G" labelled products.

Table 2: Sales-weighted price and market share of appliances, breakdowns by energy efficiency class

Energy efficiency rating	Sales-weighted average price	Market share
A++	392.3	0.03%
A+	294	3.38%
A	324.7	57.87%
B	267.3	25.82%
C	237.2	12.43%
D	313.6	0.48%
E	257	0.01%

Notes. Source: GfK, made available by Defra. Survey years: 2002-2007. 2,265 observations. No observation with energy efficiency rating of "F" or "G".

We now explain how we derive the electricity cost variable from this data. Recall that:

$$C_{jt} = \Gamma_j \times \sum_{s=1}^{L_j} \frac{q_{t+s}^f}{(1+r)^s}$$

As indicated earlier, C_{jt} should be viewed as the valuation of cost by a sophisticated and informed decision maker. This hypothetical consumer knows the annual energy consumption of each model (Γ_j) and its lifetime (L_j), which are available in the market. He considers the opportunity cost of capital when determining the appropriate discount rate. Assuming that consumers do not purchase refrigerators on credit (the average purchase price in our sample is £ 394), the opportunity cost is related to the return that could be realized on savings. Accordingly, we set the discount rate r to the real average bond deposit rate of U.K. households (2.83% according to the Bank of England for the period 2002-2007).[14] This is a conservative assumption as the benchmark rate will be higher for consumers buying on credit.

Measuring the forecasted electricity price q_{t+s}^f is more problematic as we only observe real electricity prices. We consider that a perfectly rational consumer calculates future electricity prices based on the entire series of past prices. We approximate this calculation process by an autoregressive integrated moving-average model (ARIMA) on monthly data on real electricity prices. This technique allows us to recreate the entire flow of future expected electricity prices that enter Eq. (2). The best fit with our data is obtained with an ARIMA process with one lag for the autoregressive term and one lag for the moving-average term:

$$q_t = a + bq_{t-1} + c\vartheta_{t-1} + \vartheta_t$$

[14] The nominal rate was 4.61% and the Bank of England code for the statistics is IUMWTFA. We subtracted the average inflation rate of 1.78% between 2002 and 2007.

where a, b and c are parameters and ϑ_t is the error term at time t. The model is used recurrently to make forecasts, using predictions of the previous periods to calculate new predictions. We re-estimate this model for each year to allow decision-makers to use all data that is observed at each time period. This implies that the model is updated in each year based on previous market data; e.g. the price expectations for consumers in 2003 are based on prices up until Dec. 2002). We then calculate the forecasted prices as:

$$q_{t+s}^{f} = \hat{a}_t + \hat{b}_t q_{t+s-1}^{f} \tag{5}$$

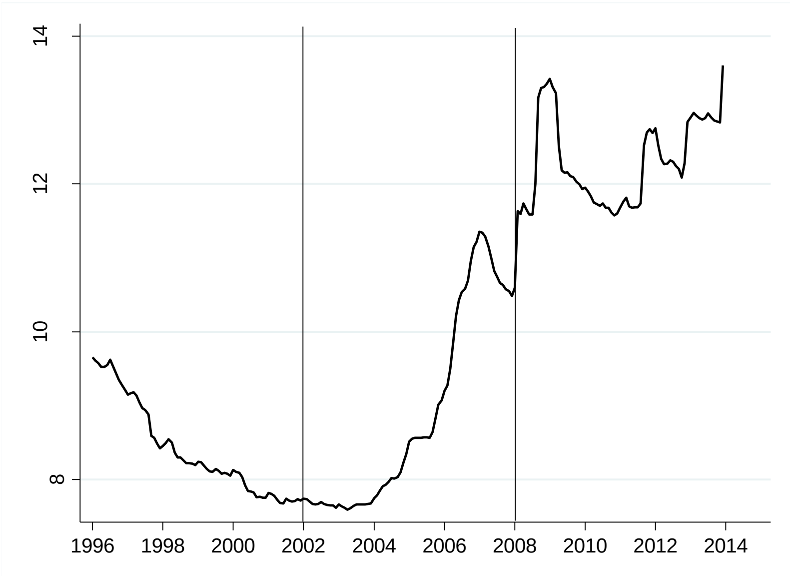
where $\hat{a}_t$ and $\hat{b}_t$ are estimates of a and b using all the data available on electricity prices up to time *t*. The detailed results of the ARIMA models are in Appendix (A7).

In Appendix A8, we develop an alternative approach in which forecasts are derived from the futures prices in the wholesale electricity market. The intuition for this approach is that the futures market aggregate information on future prices initially owned by sophisticated market participants. These results are similar to the ones we get when using the ARIMA model. Another alternative would be to proxy the forecasted electricity price by its current price. In a recent paper, Anderson et al. (2013) show that US consumers tend to believe that gasoline prices follow a random walk, so that the current price is a martingale. However, this approach is not consistent with the assumption we make since we do not want C_{jt} to capture real-world expectations, but to describe cost valuation by a sophisticated decision maker so that the parameter γ only captures the size of the deviation from this benchmark.[15]

[15] We do, however, provide the results in Appendix A8 under this alternative assumption as a test of robustness. This leads to an increase of the size of γ (and thus to reduce myopia).

Figure 1 presents the real monthly electricity price data which is calculated using data on retail electricity prices from the Department of Energy and Climate Change (DECC, 2013a). Note also that the study period 2002-2007 is marked by a dramatic rise in the electricity price driven by increasing gas prices (about 8% per year) after a period of decreases during the pre-2002 period. Consequently, forecasts are consistently below actual prices during the period, i.e. an error that decreases the size of γ).

Figure 1: Average monthly electricity prices in the UK, 1996-2014



Note: Prices in pence with CPI=1 in 2005. The study period is between the two vertical lines.

5. Estimation

In this section, we specify the different equations and discuss identification issues.

Sales. To derive an econometric specification for sales, we add year dummies λ_t to Eq. (1) and then take the first-differences in order to eliminate the share of the outside option, the value of usage and any shift in the overall market share level. This leads to:

$$\Delta\ln(s_{jt}) = -\alpha(\Delta p_{jt} + \gamma\Delta C_{jt}) + \sigma\,\Delta\ln(s_{j(g)t}) + \Delta\lambda_t + \Delta\xi_{jt} \quad (6)$$

where Δ is the first-difference operator and ξ_{jt} is the econometric error term capturing unobserved time- and product-varying heterogeneity.

A concern with eq. (6) is that the purchase price p_{jt} is endogenous since quantities and prices are simultaneously determined in market equilibrium. The origin of this problem is that unobserved time-varying product characteristics affect both consumers' product valuation and prices, i.e. $E[p\xi] \neq 0$. The log of the within-nest market share $\ln(s_{j(g)t})$ is also endogenous. A higher value of ξ increases the sales of refrigerator j and because this product belongs to nest g, an increase in s_{jt} mechanically increases $s_{j(g)t}$.

The problem might not be too severe, since first-differencing already controls for the correlation between prices and the linear component of product-specific unobserved quality that do not vary over time. The source of bias is further limited by the fact that there are a large number of product-by-year combinations in each nest. An instrumental variable approach is nevertheless adopted. Another reason for doing so is to circumvent potential measurement errors in the price variable since we do not observe transaction prices but a national average transaction price calculated by GfK.[16]

To construct the instruments, the classical approach in industrial organisation has taken advantage of the fact that the market is imperfectly competitive. In such situations it is claimed that characteristics of products $k \neq j$ influence p_{jt} but not the utility V_{jt}. Berry (1994) suggests using the nest structure of the model. His proposed instruments are the averages for different product features within and/or out of the nest that product j belongs

[16] This problem is likely to be less severe than in the auto market where list prices can widely diverge from the prices that are actually paid after commercial negotiations.

to. This approach is extended in Berry et al. (1995).[17] A weakness of these strategies is that taste shocks that affect the other products can also influence utility of product j. For instance, marketing efforts by a firm can induce a taste shock that affects all its products, or a given characteristics that concern several models might become popular among consumers. In this respect, the fact that refrigerators are quite standardized products, except in the dimensions we base the nests on, is not necessarily advantageous. It means that unobserved product characteristics are going to be correlated across nests and manufacturers. The underlying general problem is that we would ideally like to use variables that shift cost but that are uncorrelated with the demand shock, but quality variables affect both utility and production costs.

Our solution is to use instruments based on the price of products sold in two outside markets: the upright freezer market (i.e. excluding the chest freezer market) and the washing machine market. Freezer and washing machines present two useful characteristics. First, they are sold outside the refrigerator market, and thus to different consumers. One can thus assume that taste shocks are less likely to be correlated. Second they share some technical similarities with refrigerators as they are all large household appliances. Finally, and importantly, some shocks affecting production costs – e.g., an increase in steel price – are likely to be correlated across these markets.

We do not use the price of freezers and washing machines directly as instruments. Doing so would produce instruments that are insufficiently correlated with prices of refrigerators.

[17] They use the observed product characteristics (excluding price and other potentially endogenous variables), the sums of the values of the same characteristics of other products offered by that firm (if the firm produces more than one product), and the sums of the values of the same characteristics of products offered by other firms.

Instead, we use the implicit price of two characteristics that also differentiate refrigerators: capacity and whether the appliance is built-in or freestanding. These implicit prices are estimated using a hedonic pricing model on product-level data for the UK freezer and washing machine markets between 2002 and 2007 obtained from GfK. Importantly, we include brand-specific time trends in this model that allow us to control for changes in brand-specific marketing strategies and image. This ensures that the by-year-by-category of appliance (large/small and built-in/freestanding) fixed effects are not capturing changes in brand image, which could be correlated with the sales of all types of appliances, including refrigerators. To ensure that our estimation is not biased by changes in the retail sector, trade brand products have been withdrawn from the sample used to estimate the implicit price of the two attributes. All the details of how these instruments are constructed are included in Appendix A2.

As previously evoked, another potential concern is that, as data on refrigerators are only available at the national level, we use the national average electricity price to compute C_{jt}. This potentially creates a measurement problem as the price of electricity may be different from one region to the other. These differences are likely to be modest, however. In 2013, statistics show that regional differences are within ±5% of the national average, except for Northern Ireland where less than 3% of the UK population reside. In Appendix A9, we give results with a specification where the operating cost is instrumented with its lagged values to mitigate this potential measurement problem and find little differences.

A final issue is that we only have access to the average U.K. electricity prices whereas perfectly rational consumers should not care about average prices, but only consider marginal prices. The results of our base model are not biased provided that the level of the fixed part of the tariff has not changed between 2002 and 2007, which is plausible as the increase was driven by gas price increases which raised the (variable) cost of electricity generation. However, in Appendix A8 we run a robustness check where we assume that the *share* (not the level) of the fixed part remains stable. This slightly inflates the size of γ.

The price equation. We also express Eq. (5) in first differences:

$$\Delta p_{jt} = -\eta \Delta C_{jt} + \Delta \lambda_{b(j)t} \quad + \Delta \epsilon_{j,t} \tag{7}$$

In order to properly identify the parameter η, we need to control for supply and demand factors, except the electricity cost, that vary over time and across products. On the demand side, this is the utility component ξ that we have discussed extensively above. On the supply side, the main omitted variable is the time-varying component of product j' production cost. The price is also influenced through competition by other product characteristics. The problem is that the controls that are available, in particular the product characteristics of similar products, are likely to be endogenous, and the instruments are not strong enough to include those. To mitigate this problem, we have included by brand by year fixed effects. Our view here is that most shocks on taste and production cost are likely to be brand-specific as products from the same brand are produced and marketed by the same firm. Nevertheless we provide the results using average characteristics from similar appliances as control variables in Appendix A6.

The product availability equation. For convenience, we rewrite the equation here:

$$d_{jt} = \Phi(k_d d^*_{jt-1} + k_p p_{jt} + \ k_c C_{jt} + \lambda_t + \theta_j) \tag{8}$$

We use the method suggested by Wooldridge (2005) to estimate this dynamic probit model. The correlation between the random effect θ_j and the initial value $d^*_{j,0}$ is made explicit. In our case, this gives:

$$\theta_j = k_0 + k_1 d^*_{j0} + k_z Z_j + \mu_j. \tag{9}$$

Z_j is the row vector of all non-redundant explanatory variables in all time periods. It includes time-constant product features (e.g., size or energy efficiency rating) but also the purchase price of products at each time period (i.e., the price in 2002, in 2003...). To avoid multicollinearity, we exclude year dummies and only include the running cost for one year because they are calculated from Γ_j, which does not vary over time. k_0 and k_1 are parameters, k_z is a vector of parameters and μ_j is a random effect such that $\mu_j|(d_{j0}^*, Z_j)$ follows a normal distribution.

Substituting Eq. (8) into Eq. (9) leads to a random-effect probit model except that d_{j0}^* and Z_j are included as explanatory variables:

$$d_{j,t} = \Phi\left(k_d d_{jt-1}^* + k_p p_{jt} + \ k_c C_{jt} + k_0 + k_1 d_{j0}^* + k_z Z_j + \mu_j + \lambda_t\right) \qquad (10)$$

The estimation of Eq. (10) poses two problems. The first is that the information on p_{jt} is missing in the data for all the periods when product *j* is not available on the market ($d_{jt}^* = 0$). We thus need to make an assumption about the purchase price of this product in the years when it is unavailable on the market. For all the products that are not commercialized at time t, one could perform a regression on observed purchase prices (when $d_{jt}^* = 1$) and produce out-of-sample predictions for p_{jt} when $d_{jt}^* = 0$. However, this would underestimate the standard error of the estimated coefficients as we would be using imputed values for p_{jt} as if they were observed values. The second problem is that the purchase price of appliances and the probability d_{jt} are simultaneously determined, implying that p_{jt} is endogenous.

To solve these problems, we perform multiple imputations for each missing p_{jt}, a technique which allows calculating unbiased standard errors for the estimated parameters (Rubin, 1987). The procedure is as follows. First, we look at the distribution of purchase prices p_{jt}

and perform a transformation on p_{jt} so that the transformed purchase prices follow a normal distribution.[18] The transformation that we use is:

$$\tilde{p}_{jt} = \ln\left(\left[p_{jt}\right]^{n_0} - n_1\right) \qquad (11)$$

$\tilde{p}_{jt}$ are transformed prices, n_0 and n_1 are parameters that ensure that the skewness of the distribution is close to 0 and its kurtosis around 3, which are two properties of normal distributions. In our case, we set $n_0 = 2$ and $n_1 = 1736$.[19] Then, we run a fixed effect linear regression on transformed prices:

$$\tilde{p}_{jt} = h_j + h_c C_{jt} + h_W W_{jt} + \lambda_t + x_{jt}$$

h_j is the product specific fixed effect, λ_t the time fixed effect, h_c is a parameter and x_{jt} is the random error term. Importantly, W_{jt} corresponds to the vector of instruments that have been used to control for the sales-price endogeneity and h_W is a vector of parameters. Using these instruments in the imputation process allows us to control for the endogeneity on imputed purchase prices. We denote $\hat{p}_{jt}$ the predictions obtained from this regression.

Based on the results of the linear regression, we create ten imputed prices for each missing value of p_{jt}. Let *m* denote the imputation number, then each imputed transformed price of product *j* at time *t* is given by:

$$\tilde{p}_{jt}^{m} = \hat{p}_{jt} + x_{jt}^{m},$$

where x_{jt}^{m} is a randomly assigned and normally distributed error term corresponding to imputation *m* for product *j* at time *t*. Next, we use Eq. (11) the other way round to calculate the value of the imputed prices p_{jt}^{m} from their transformations $\tilde{p}_{jt}^{m}$. This step allows us to

[18] The multiple imputation method is known to be biased if applied to non-normally distributed variables.
[19] We have performed the Skewness and Kurtosis test on $\tilde{p}_{j,t}$. The p-values of this test is 0.35. It therefore does not reject the hypothesis of normality of $\tilde{p}_{jt}$.

obtain imputed values $p_{j,t}^{m}$ with a distribution that is close to the distribution of observed prices. Once the p_{jt}^{m} values have been obtained, we estimate Eq. (10) as many times as there are imputations and then compute coefficient values and standard errors that take the uncertainty surrounding the value of p_{jt} when $d_{jt}^{*} = 0$, into account.

The technique described above also solves the second problem as it allows us to obtain consistent imputations that take the endogeneity of purchase prices into account. To control for the endogeneity of observed purchase prices, we run a linear regression similar to what was described earlier and extract predicted values that we use later in the dynamic probit model instead of using observed prices.

6. Results

Sales. Table 3 reports estimation results of Eq. (6). As there is an interaction between α and γ, we use a GMM estimator to parameter values and standard errors.[20] The value of σ (0.89 and significant at 1% level) indicates that the within-nest correlation is substantial. Additionally, the coefficient for the valuation of money has the expected sign and is significantly different from 0.

The main result in Table 3 is that $\gamma \approx 0.57$, which implies that consumers underestimate energy costs by 40%. They still take a large share (57%) of future discounted operating costs into consideration when purchasing a refrigerator. Importantly, the 95% confidence interval for γ is 0.31 – 0.82. Hence the estimate of the attention parameter is both statistically different from 0 and 1. Another way of presenting this result is to compute the "implicit"

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[20] The standard empirical approach is to separately estimate the coefficients for the price and the energy costs in a linear setting, and deduce from it the values of α and γ. We include the results obtained with the standard linear approach as a test of robustness in Appendix A3.

discount rate which would rationalize consumer behavior. That is, the value of r necessary to obtain a value of γ equal to one. We show in Appendix A4 that the implicit discount rate is 11%. Therefore, consumers behave as if they used a discount rate of 11% to compute the net present value of electricity cost, which is arguably at moderate distance to the average real bond deposit rate during the study period (2.83%).

Table 3: First difference IV-GMM estimation results of the sales equation

Dependent variable	Logarithm of market share of product *j*
Importance of total electricity costs (γ)	0.5671*** (4.32)
Utility for money (α)	0.0052*** (3.51)
Within-group correlation of error term (σ) for the demand equation	0.889*** (16.14)
Year dummies	Yes
Observations	1,365

Notes. Two instruments are used. They correspond to the fixed effects capturing year-by-year changes in the price of upright freezers and washing machines. The nests on which σ is calculated distinguish refrigerators from combined refrigerators-freezers, built-in from freestanding appliances, and appliances by capacity (over and below the sample median). *t*-statistics in brackets. Standard errors are robust to heteroskedasticity and clustered on products. Results marked with *, ** and *** are statistically significant at 10%, 5% and 1%, respectively.

This implicit discount rate is clearly low when compared with the earlier literature on refrigerators, which have found implicit discount rates above 30% (with the only exception being Tsvetanov and Segerson, 2014). As outlined above, there are two likely explanations. The first is that previous estimations use older data. Since then, investment inefficiencies may have reduced because consumers are better informed: energy labeling is mandatory for refrigerators since 1995 in the European Union. This is in line with the views expressed by many observers who consider that the EU Energy Label has been very successful in reducing the information gap about energy efficiency (see for example Atkins and ECN, 2006). The second explanation is methodological. We use panel data techniques that better control for unobserved product differences. In this respect, when we use a hedonic pricing model on a cross section of models, i.e. the approach popularized by Hausman (1979), we find a discount rate of 210% (detailed results provided in Appendix A5). As argued in Section 2, recent studies that rely on panel data tend to find rates of similar magnitude.[21]

The average effect obtained with this base specification is robust to changes in the parameters used to calibrate the GMM model: the sensitivity analysis with different values of product lifetimes, electricity prices and nest structures presented in appendices (A1 and A8) show little differences in the magnitude of the implicit discount rate.

Price. Estimation results are shown in Table 4. We simply use first differences and cluster-robust standard errors to estimate this equation with ordinary least squares. As expected, producers adapt retail prices to the electricity costs: an increase by £1 in future electricity costs reduces the sales price of an appliance by £0.44. Three quarters of the perceived increase in future operating costs are therefore compensated for by a decrease in the purchase price of appliances.

Table 4: Estimation results of the price equation

Dependent variables	Price of product *j*
Discounted electricity costs, η_1	-0.444***
	(-2.9)
Year x brand dummies	Yes
First differences	Yes

[21] Tsvetanov and Segerson (2014) find slightly higher rates for refrigerators (13-22%), but they use a cross section of US households.

Dependent variables	Price of product *j*
Observations	1,365

Notes. *t*-statistics in brackets. Standard errors are robust to heteroskedasticity and clustered on products. Results marked with *, ** and *** are statistically significant at 10%, 5% and 1%, respectively.

Product availability. Results for the dynamic probit model are reported in Table 5. They confirm the assumption that an increase in the electricity costs reduces the probability that the product is commercialized. Thus, highly energy-consuming products – energy-inefficient products and large refrigerators – are more likely to exit the market when electricity prices increase.

The other estimated parameters have the expected signs. For example, there is high probability that a product is commercialized if it was on the market the year before: the coefficient is both high and highly statistically significant. Conversely, a product available in 2002 is more likely to be obsolete in the future years and therefore to disappear during the sample period. Likewise, products with a price that is relatively high tend not to be commercialized. This result is statistically significant at 1%. Conversely, any reduction in the purchase price of an appliance increases its probability of being kept on the market. This is important because we have previously found that suppliers reduce the price of energy inefficient appliances when electricity prices increase. Such reductions in the purchase price may therefore preserve inefficient products on the market when electricity prices go up.

Table 5: Dynamic panel data probit estimation of product availability based on Wooldridge (2005)

Dependent variables	Availability of product *j*: d_{jt}^{*}
The product was commercialized the year before (k_d)	0.9013*** (30.25)
Imputed appliance price (k_p)	-0.0017*** (-11.72)
Expected and discounted running costs (k_c)	-0.0016** (-2.24)
The product was commercialized in 2002 (k_1)	-0.3578*** (-10.36)
Non-redundant explanatory variables covering all time periods and including time-constant product features (k_z)	Yes
Year dummies	Yes
Observations	10,280
Number of imputations for appliance prices	10

Notes. *t*-statistics in brackets. Standard errors are robust to heteroskedasticity, clustered on products, and take into account uncertainty regarding the imputed values of appliance prices. Results marked with *, ** and *** are statistically significant at 10%, 5% and 1%, respectively.

7. A simulation of electricity price increase

If further energy efficiency improvements in domestic appliances are to form part of overall energy or CO_2 reduction strategies – and there are many reasons to believe that it should be[22] – the above results offer useful insights. Specifically, it enables quantifying how energy use from durable goods responds to energy price changes, taking both consumer and producer responses into account. In this section, we simulate the effect of a 10% increase in

[22] One reason is that, for 2020, the European Union has a target of 20% savings in its primary energy consumption compared to projections. Energy efficiency is one of the means to achieve this objective. In 2011, the European Commission estimated that the EU was on course to achieve only half of the objective (European Commission, 2011a).

the price of electricity. Recall that the above results describe three adjustments: consumers adjust their purchase behavior; suppliers modify prices and revise their product portfolio. Likewise, our simulation builds up on these three impacts.

To assess the short run impact of an electricity price shock on market shares, we use the estimates of the sales equation to predict product *j*'s market shares s_{jt}. Based on the values obtained for each product *j* at time t, we calculate the market averages for the purchase price, the electricity costs, the capacity and the energy consumption (in kWh/year) of sold appliances in both a baseline scenario (with historical prices) and a scenario with a 10% increase in the electricity price. To evaluate the medium term impact associated with retail price adjustments, we use the purchase price equation to predict the impact of the electricity price increase on p_{jt}. We then recalculate market shares with the new prices. Finally, we introduce changes in the product availability by using the results of the dynamic probit model for product availability. More precisely, we compute the predicted probabilities that each product *j* in our sample is available on the market at the baseline price and then at the 10% higher electricity price. We denote these probabilities $\hat{d}_{jt}$ and $\hat{d}_{jt}^{10\%}$, respectively, then calculate their ratio ($\hat{d}_{j,t}^{10\%}/\hat{d}_{j,t}$), which we use to weight the market shares of each product *j* in the scenario with a 10% electricity price increase.[23]

We need to make three additional assumptions. First, we assume that the increase in the price of electricity does not have any impact on the total amount of sold appliances.[24] This is

[23] In the simulations, we only use the observations for which we have predictions for market shares and prices. Furthermore, $\hat{d}_{j,t}^{10\%}$ is inclusive of the impact of the electricity price shock on both running costs and purchase price adjustments. However, it is not computed in a dynamic fashion: we do not take into account the fact that $\hat{d}_{j,t}^{10\%}$ has an influence on $\hat{d}_{j,t+1}^{10\%}$, $\hat{d}_{j,t+2}^{10\%}$, etc.

[24] Our model cannot predict the evolution of the outside goods market share as it is absorbed by the time dummies. Therefore, it is not possible to determine how the total amount of sold appliances would evolve.

not unrealistic since purchases of refrigerators are mostly replacements and households are unlikely not to purchase any refrigerator because of an increase in the price of electricity. However, increases in the price of electricity could temporarily trigger additional purchases by consumers who possess relatively energy-inefficient products and therefore want to replace them: this transitional effect is not taken into account in these simulations. Second, our specification uses expected rather than real electricity prices. In order to calculate the impact of a price increase, we assume that expected electricity prices would rise proportionally with real electricity prices (i.e. by 10%). Third, we neglect the impact of changes in the size of nests on the market shares of individual products since this effect is likely to be very small.

Simulation results are displayed in Table 6. The long-run elasticity of energy consumption to electricity price is rather low: -0.1 after accounting for both demand and supply adjustments. Consumer myopia marginally explains this pattern. Recall that the attention parameter is about 0.57, meaning that a 10% increase in electricity cost corresponds to a 5.7% increase if consumers were fully rational. This explains why, in the short run, the energy consumption of sold appliances decreases by 2.1%. See column (i) in Table 6.

But the differences between short-, medium-, and long-term elasticities also show the importance of supplier behavior. In particular, price revisions by suppliers drastically reduce the impact on energy use: the elasticity after price adjustment falls to -0.5. On the other hand, product innovation reduces energy consumption as the products available in the market use less energy on average after changes in product availability. The impact is high as innovation doubles the elasticity.

Table 6: Simulated impacts on average annual energy consumption of a 10% increase of the electricity price

Sales-weighted averages	Electricity price 10% higher		
	Short term impact on market shares (i)	After price adjustments (ii)	After price adjustments and change in product availability (iii)
Variation in levels	-6.6 kWh/year	-1.5 kWh/year	-3.0 kWh/year
Variation in %	-2.1%	-0.5%	-1.0%

As explained above, the negative impact of price adjustments on energy use is driven by the fact that energy-intensive products experience larger cuts than energy efficient products. In this way, suppliers compensate for more of the increase in discounted electricity costs for low-efficient appliances. This is visible in Table 7 that displays the long run simulation results with a breakdown by energy efficiency class. Demand only shifts from low- to high-efficiency appliances to a limited extent. As explained above, this supply-driven rebound effect is made possible by the fact that the market is imperfectly competitive due to product differentiation. In a competitive market where the price equals the marginal cost of production, producers would have less latitude in their pricing strategies.

Table 7: Simulated impacts of a 10% increase of electricity price by energy efficiency class

Energy efficiency rating	Relative change in prices	Relative change in sales
A++	-2.0%	3.5%
A+	-4.0%	1.9%
A	-5.6%	0.1%
B	-7.0%	-0.2%
C	-8.2%	-0.9%
D	-6.4%	1.3%
E	-14.0%	-6.2%

Notes: The relative change in sales is based on the total market share of each energy efficiency class, the relative change in prices on the sales-weighted average price within each energy efficiency class. For example, sales of "A+" appliances increase by 1.9% with a 10% electricity price increase, and their average price decrease by about 4.0%.

The analysis thus highlights how imperfect competition dampens energy price signals in the refrigerator market, leaving suppliers ample room for maneuver to undertake asymmetric price adjustments. This is done in order to cushion the effect that higher electricity price would otherwise have, on their low energy-efficient products. It is then worth calculating how high the price elasticity of energy demand would have been, had these inefficiencies not be present. Results are displayed in Table 8 where our results are compared with a hypothetical scenario where consumers are perfectly rational ($\gamma = 1$) and suppliers do not change prices. The long-term elasticity would be 5.5 times greater if these inefficiencies were to be removed (from -0.1 to -0.55). The table also illustrates how the inefficiency related to imperfect competition is larger than the impact of consumer myopia: the long-term elasticity is -0.17 with imperfect competition and perfect rationality and -0.31 when consumers become myopic under perfect competition.

Table 8: Impact of a 10% electricity price increase on energy consumption depending on the types of market failure and market competition

Relative impact on energy consumption	Myopic behavior (only 57% of energy costs are perceived)	Rational behavior (all energy costs are perceived)
Imperfect competition (suppliers adjust appliance prices)	-1.0%	-1.7%
Perfect competition (no ability to adjust appliance prices)	-3.1%	-5.4%

These simulations convey two important messages. First, imperfect competition appears to be a more serious problem than myopic behavior for the social planner attempting to increase energy efficiency of domestic appliances. Even if consumers value the future cost of energy consumption correctly when they purchase appliances, taxing energy would still have an attenuated impact in this market because suppliers are able to cushion the impact of electricity price shocks on the sales and obsolescence of the most energy consuming appliances. It should be noted that the two inefficiencies are partly “substitutes” in the sense than an increase in the size of one reduces the importance of the other. So, if consumers are less myopic, the suppliers’ incentives to reduce the price of inefficient models are higher, and vice-versa.

Second, the impact of electricity price shocks on product innovation can be relatively important. In our case, omitting the innovation stage would lead to an underestimation of the elasticity of energy consumption to electricity prices by about 50%. This implies that the two identified sources of market inefficiencies not only have short-run impacts on the sales of energy efficient durable goods, but also long-lasting effects on product availability and hence the suppliers’ incentives to innovate..

8. Conclusion

While the empirical literature on the impact of energy prices on energy efficiency in the residential sector has primarily focused on consumer behavior, this paper develops a comprehensive view of both demand-side and supply-side adjustments that occur in the UK refrigerator market in response to electricity price changes.

We obtain results which tend to moderate the importance of consumer myopia as a barrier to energy efficiency investments, which has dominated the debate thus far. We find that consumers undervalue future energy costs by 43%, which is equivalent to applying an implicit discount rate of 11% to the stream of future electricity costs when calculating the net present value. This result is robust to many factors, in particular the average lifetime of appliances and expected energy prices. The use of panel data is probably the main reason why the rate why our implicit discount rate is lower compared to what has been reported previously which ranged from 39% to 300% (see Section 2). When specifying a hedonic pricing model on a cross section of models and using the approach adopted by Hausman (1979), we instead find a discount rate of 210%.

Our results bring light to the importance of another market failure: as competition in the refrigerator market is imperfect, manufacturers and retailers are able to partly absorb electricity price shocks, by lowering the relative purchase price of the least energy-efficient appliances. We estimate that price cuts compensate for more than one half of the electricity price increase. As a result, while in the short run – holding supply factors constant – a 10% electricity price rise induces a 2.1% decrease of energy consumption, the impact falls to 0.5% after product price adjustments. At the same time, we also find evidence that the innovation response by manufacturers is strong in that a rise in electricity price significantly affects the probabilities of inefficient models to exit the market and of new efficient products to be launched. This innovation effect leads to a 1.0% decrease of energy use in the long run.

What policy implications can be drawn from these results? The first is obvious: inefficiencies are sizable and they justify the need to complement energy taxation with other instruments to promote energy efficiency investments; these complementary policies should cope with both demand- and supply-side issues. Evaluating the welfare properties of the different policy options is then clearly beyond the scope of this paper, in particular because we use reduced-form supply equations, but several remarks can be made nonetheless.

To start with, our findings suggest that the EU energy label policy has been able to partly mitigate investment inefficiencies as consumer myopia is shown to be limited. Yet, our analysis shows that labeling policies alone is unlikely to address the energy efficiency gap.

Specifically, it fails to account for an important source of inefficiency identified in this paper i.e. the asymmetric price responses by suppliers. Labeling may even exacerbate the problem as suppliers are incentivized to subsidize low energy efficiency-performing models. A tax on inefficient models combined with a subsidy for efficient ones (e.g. feebates or bonus/malus schemes) would correct this problem. Efficiency performance standards where the influence on price is more indirect are less likely to be effective. Another argument against the use of direct regulation is that while the impact on product renewal is often viewed as a strength of the regulatory approach, we find that energy prices are able to significantly induce product innovation.

Finally, we are aware of the risks of transferring these results to other products, regions and periods. We do, however, think that the mechanisms highlighted in the present work operate in many markets of energy-using durables where product differentiation is pervasive.

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Appendix

A1. Alternative choices for the nests

A weakness of the nested logit approach is the fact that the nest structure is arbitrarily chosen by the econometrician. To check the robustness of our results to the choice of nests, we run the estimations of the sales equation with alternative nests and report the results in Table 9. The estimate of γ varies across specifications, but remains below 1.

Table 9: First difference GMM estimation results of sales with alternative nests

Dependent variable: log. market share of product j				
Nests based on:				
refrigerators vs. refrigerators-freezers	No	Yes	Yes	No
Over/below median capacity	No	Yes	No	Yes
Built-in/freestanding	No	No	Yes	Yes
Importance of total electricity costs (γ)	0.6288** (2.26)	0.5595*** (4.1)	0.2319 (1.24)	0.5966*** (4.47)
Utility for money (α)	0.0083 (1.63)	0.0045*** (3.41)	0.0023*** (2.89)	0.0046*** (3.48)
Within-group correlation of error term (σ) for the demand equation	n/a	0.8588*** (17.82)	1.075*** (25.33)	0.8933*** (16.72)
Year dummies	Yes	Yes	Yes	Yes
First difference	Yes	Yes	Yes	Yes
Observations	1,365	1,365	1,365	1,365

Notes. Two instruments are used. They correspond to the fixed effects capturing year-on-year changes in the price of upright freezers and washing machines. *t*-statistics in brackets. Standard errors are robust to heteroskedasticity and clustered on products. Results marked with *, ** and *** are statistically significant at 10%, 5% and 1%, respectively.

A2. Construction of the instruments for the sales equation

To calculate the implicit price of the two attributes (capacity and built-in vs free-standing), a hedonic pricing model is used (see the results in Table 10). We run two regressions, one for freezers, and one for washing machines, to capture the evolution of the price of each subcategory of refrigeration appliance. This is done by including year-'category of appliance' (large/small and built-in/freestanding) specific fixed effects.

In addition, we include product specific fixed effects that control for all time-invariant product features and therefore for any difference in the sample of appliances that we observe from one year to the other, and could be susceptible to bias the estimation of the evolution of the average price of the various subcategories of appliances. As explained previously, we also include brand-specific time trends that control for the general development of brand-specific marketing strategies.

We assign weights to each product *j* in our regressions. We do so to ensure that the regression results are representative of the market and to reduce the risk of measurement error on the average price of each model. The weights are identical for all the observations of product *j* between 2002 and 2007, and correspond to the average of all the sales registered by product *j* between 2002 and 2007.

Finally, we trim outliers in the final sample used for the regressions: we identify the 2.5% products with either largest or smallest price, capacity or energy consumption, in addition to the 2.5% of products with highest sales levels. Any product that falls within at least one of these categories is dropped.

Table 10: Hedonic regressions to construct the instruments (freezers and washing machines)

Dependent variable	Price of washing machines	Price of freezers
By year, by category of appliance fixed effects		
Small, 2002 (built-in for freezers)	0	0
Small, 2003 (built-in for freezers)	-42.5061*** (-3.11)	-2.5749 (-0.12)
Small, 2004 (built-in for freezers)	-75.2039*** (-2.85)	-11.508 (-0.31)
Small, 2005 (built-in for freezers)	-125.6751*** (-3.18)	-16.0016 (-0.29)
Small, 2006 (built-in for freezers)	-159.7466*** (-3.05)	-43.4277 (-0.6)
Small, 2007 (built-in for freezers)	-205.2927*** (-3.13)	-38.6044 (-0.45)
Large, 2002 (built-in for freezers)	37.824 (1.45)	10.3909 (0.24)
Large, 2003 (built-in for freezers)	-3.9397 (-0.12)	1.2222 (0.03)
Large, 2004 (built-in for freezers)	-57.4207 (-1.59)	13.543 (0.31)
Large, 2005 (built-in for freezers)	-128.0074*** (-2.94)	4.5595 (0.08)
Large, 2006 (built-in for freezers)	-174.3192*** (-3.18)	12.0702 (0.17)
Large, 2007 (built-in for freezers)	-218.5002*** (-3.24)	-14.9726 (-0.18)
Small, 2002 (freestanding, freezers only)		-18.8481 (-0.46)
Small, 2003 (freestanding, freezers only)		-18.4543 (-0.42)
Small, 2004 (freestanding, freezers only)		-5.8397 (-0.11)
Small, 2005 (freestanding, freezers only)		-7.9437 (-0.13)
Small, 2006 (freestanding, freezers only)		15.2585 (0.2)
Small, 2007 (freestanding, freezers only)		19.0729 (0.21)
Large, 2002 (freestanding, freezers only)		8.3791 (0.28)
Large, 2003 (freestanding, freezers only)		-2.8049 (-0.08)

Large, 2004 (freestanding, freezers only)		9.7592 (0.21)
Large, 2005 (freestanding, freezers only)		17.6663 (0.3)
Large, 2006 (freestanding, freezers only)		27.5309 (0.38)
Large, 2007 (freestanding, freezers only)		29.2075 (0.33)
Fixed effects	Yes	Yes
Brand-specific time trends	Yes	Yes
R^2	0.31	0.28
Number of observations	1,637	851

Notes. *t*-statistics in brackets. Standard errors are robust to heteroskedasticity and clustered on products. Results marked with *, ** and *** are statistically significant at 10%, 5% and 1%, respectively. 'Small' means below sample median, 'Large' is above. Regression is weighted for each observation of product *j* by the total sales of product *j* over 2002-2007.

A3. Linear specification for the sales equation

A standard approach in existing literature is to use a 2SLS estimations of the sales equation. Using the 2SLS with our data can have two objectives: 1) check the robustness of our results based on the non-linear specification and 2) perform standardized tests to control that the instruments are valid and strong.

Results are presented in Table 11 for three different approaches. The left column is the first-difference estimation with our two main instruments. The middle includes a third instrument which is the squared value of the freezer-based instrument. The right column is the fixed-effect estimation with the two main instruments. We assess the strength of the instruments used with the two regressions with two instruments using an under-identification test and a weak identification test. We also test for over-identification, using the regression with three instruments,

In the linear cases, the coefficients for the purchase price and electricity costs are negative and statistically significant at the 1% level. This implies that a representative consumer would underestimate energy costs by 31-43%. These values are in line with the 43% that we had estimated in the base specification. In addition, results show that the instruments exhibit the necessary properties as they pass all three tests (for under-identification, weak identification and over-identification).[25]

[25] Note that there exists no reference values for the weak identification test under heteroskedasticity. In fact, the Stock-Yogo (2005) critical values only apply to homoskedasticity. They can only be used as a general reference. Therefore, we are confident that the estimation is not weakly identified considering that the Kleibergen-Paap rk Walf F statistic, that takes heteroskedasticity into account, provides a result above the critical value for 5% maximal IV relative bias. Furthermore, the IV regression was run assuming homoskedasticity.

Table 11: Linear IV regressions for the sales equation, using either first differences or fixed effects

Dependent variable:	First differences; 2 instruments	First differences; 3 instruments	Fixed effects; 2 instruments
Price (instrumented) (A)	-0.0052*** (-3.51)	-0.0055*** (-3.71)	-0.0031*** (-4)
Log. within-group market share (σ) (instrumented)	0.889*** (16.14)	0.9043*** (17.58)	1.0628*** (22.48)
Lifetime electricity costs (B)	-0.003*** (-2.9)	-0.0031*** (-2.91)	-0.0021*** (-3.11)
Year dummies	Yes	Yes	Yes
Product level fixed effects/First differences	First differences	First differences	Fixed effects
Importance of total electricity costs, γ (A/B)	0.5671*** (4.32)	0.5578*** (4.3)	0.6857*** (3.42)
Underidentification test (p-value) Kleibergen-Paap rk LM statistic	<0.01 15.42	<0.01 15.06	<0.01 27.33
Overidentification test (p-value) Hansen J statistic	n/a	0.56 0.35	n/a
Weak identification test (Max. IV size bias) Kleibergen-Paap rk Wald F statistic	<10% 7.85	>25% 4.97	<10% 17.39
Observations	1,365	1,365	2,449

Notes. The nests on which σ is calculated distinguish refrigerators from combined refrigerators-freezers, built-in from freestanding appliances, and appliances by capacity (over and below the sample median). *t*-statistics in brackets. Standard errors are robust to heteroskedasticity and clustered on products. Results marked with *, ** and *** are statistically significant at 10%, 5% and 1%, respectively.

A4. Implied discount rate

Table 12 gives the results of the sales equation where the discount rate has been chosen to induce an estimate of gamma equal to 1. The corresponding real discount rate is 11.0%.

Table 12: First difference GMM IV estimation results with the implied discount rate inducing γ =1

Dependent variable: log. market share of product *j*	
Electricity prices	
Discount rate	11.0%
Importance of total electricity costs (γ)	1.0077*** (4.32)
Utility for money (α)	0.0052*** (3.51)
Within-group correlation of error term (σ) for the demand equation	0.8887*** (16.12)
Year dummies	Yes
First difference	Yes
Observations	1,365

Notes. Two instruments are used. They correspond to the fixed effects capturing year-on-year changes in the price of upright freezers and washing machines. The nests on which σ is calculated distinguish refrigerators from combined refrigerator-freezers, built-in from freestanding appliances, and appliances by capacity (over and below the sample median). *t*-statistics in brackets. Standard errors are robust to heteroskedasticity and clustered on products. Results marked with *, ** and *** are statistically significant at 10%, 5% and 1%, respectively.

A5. Results mimicking the standard hedonic pricing method

We run a between-effect regression on panel data using the price of appliances as the dependent variable. The between-effect estimator uses only the cross-sectional information of the data and therefore mimics a hedonic pricing approach while allowing the use of the full sample rather than rely only on a one-year cross section. With this method, we obtain $\gamma \approx 0.07$, which is far below the estimates obtained using the discrete choice model. The implies a discount rate of 210%.

Table 13: Between effect linear regression on appliance price

Discount rate	2.83%	210%
Independent variables		
Lifetime electricity costs (γ)	-0.0669 (-1.47)	-0.9995 (-1.42)
Height	1.7157*** (5.41)	1.7228*** (5.43)
Width	8.0065*** (9.84)	8.013*** (9.85)
Capacity	-0.0742 (-0.24)	-0.0751 (-0.24)
Squared capacity	0.0012*** (2.88)	0.0012*** (2.87)
Appliance is a refrigerator-freezer	-1.7401 (-0.1)	-6.8736 (-0.46)
Appliance is built-in	-184.0576*** (-20.72)	-184.0183*** (-20.72)
Appliance has a no-frost system	21.5512** (2.08)	21.1803** (2.05)
Time dummies	Yes	Yes
R^2	0.61	0.61
Number of observations	2,583	2,583

Notes. *t*-statistics in brackets. Results marked with one to three stars are statistically significant at 10%, 5% and 1% respectively.

Alternatively, when running the same specification as above but separately for each year of our data, we find the largest value of γ for year 2002, which corresponds to an implicit discount rate of 40%.

Table 14: Summary results on the value of γ from cross-sectional hedonic regressions by year

Year of the panel used	2002	2003	2004	2005	2006	2007
Lifetime electricity costs (γ)	-0.2213***	-0.2187**	-0.2049**	-0.0667	-0.0282	0.0048
	(-2.96)	(-2.58)	(-2.43)	(-0.75)	(-0.32)	(0.06)

Notes. The coefficients above come from different regressions.

A6. Alternative specifications for the price equation

If the total demand for refrigerators is inelastic, theory predicts that the price of energy-efficient goods can increase. A specification which allows us to test this assumption is as follows:

$$\Delta p_{jt} = \beta + \eta_1 \Delta C_{jt} + \eta_2 \Delta\left(C_{jt}\right)^2 + \Delta\lambda_{b(j)t} + \epsilon_{j,t}$$

where η_1 is expected to be positive while η_2 is expected to be negative. The table below gives the results obtained using this specification. The results do not confirm the hypothesis.

Table 15: First difference estimation results of the price equation assuming a non-monotonic relationship between the product price and the electricity cost

Independent variables	
Discounted electricity costs, η_1	0.4295 (0.65)
Squared discounted electricity costs, η_2	-0.0006 (-1.17)
Year x brand dummies	Yes
Observations	1,365

Notes. *t*-statistics in brackets. Standard errors are robust to heteroskedasticity and clustered on products. Results marked with *, ** and *** are statistically significant at 10%, 5% and 1%, respectively.

On the other hand, our base specification for the price equation does not control for the fact that prices are also influenced by other product characteristics through imperfect competition. In the specification below, we include the average of two characteristics of the products sold by other brands within the same nest as control variables. These two product characteristics are height and presence/absence of no-frost systems as this feature proves to have the highest correlation with the price of product j. Unfortunately, these additional control variables are likely to be endogenous and we do not possess instruments strong enough to deal with this problem.

Table 16: First difference estimation results of the price equation with the characteristics of the products from other models (but within the same nest) as control variables

Independent variables	
Discounted electricity costs, η	-0.312 (-1.57)
Average height of products of other firms within the same nest	-181.3349* (-1.96)
Share of products with no frost system from other firms within the same nest	-2.9681 (-1.4)
Year x brand dummies	Yes
Observations	1,365

Notes. *t*-statistics in brackets. Standard errors are robust to heteroskedasticity and clustered on products. Results marked with *, ** and *** are statistically significant at 10%, 5% and 1%, respectively.

A7. Estimation of electricity price forecasts with the ARIMA model

1. Testing for different ARIMA specifications

The ARIMA models can handle lags in the autoregressive (AR) term and in the moving average (MA) term. Moreover, they can be expressed in levels or in difference. We have tested for different combinations and found that the best fit was provided by an ARIMA model with a one lag AR-term and one lag for the MA-term. These results are evident from Table 17, which corresponds to the fit of various ARIMA specifications for the price expectations in 2007.[26]

Table 17: Results for different ARIMA specifications

Independent variables	Base model	(a)	(b)	(c)	(d)	(e)
Lag of autocorrelated term	0.9968*** (197.51)	0.9976*** (227.27)			0.7134*** (17.41)	
Lag of moving average term	0.5887*** (12.09)		0.9588*** (39.71)			0.5848*** (11.78)
Constant	1.1748*** (4.47)	1.180*** (4.44)	0.9772*** (72.70)	0.0015 (1.52)	0.016 (0.78)	0.015 (1.37)
Standard deviation of the white-noise disturbance	0.0077*** (25.40)	0.0099*** (27.44)	0.0536*** (14.53)	0.0098*** (25.38)	0.0069*** (25.10)	0.0077*** (25.21)
Equation in first difference	No	No	No	Yes	Yes	Yes
Number of observations	133	133	133	132	132	132

Notes. t-statistics in brackets. Standard errors are robust to heteroskedasticity with clustering of products. Results marked with one to three stars are statistically significant at 10%, 5% and 1% respectively. The models are run on the price index of electricity corrected by the consumer price index (2005 = 1).

[26] ARIMA models in table 18 only include lags at $t-1$. We have tested for the inclusion of more lags but, these models do not fit the data as well as this specification. Whether one of the coefficients of the model was no longer statistically significant, as in (c), (d) and (e) or the models were not converging for all the years for which expectations need to be modeled.

2. Results of ARIMA model for the different years for which expectations are modeled

Expectations for a given year are modeled with the data available from 1996 up to the last month of the previous year. For example, expectations in 2003 are assumed to be based on electricity price information available from January 1996 to December 2002. Table 18 presents the results of each ARIMA model used to produce price expectations for purchases that takes place in 2002, 2003, 2004, 2005, 2006 and 2007.

Table 18: Results of ARIMA models used to produce rational price expectations

Year when the forecasts are to be made	2002	2003	2004	2005	2006	2007
Independent variables						
Lag of AR-term	0.9964*** (58.85)	0.9971*** (69.98)	0.9972*** (83.93)	0.9950*** (93.06)	0.9945*** (78.12)	0.9968*** (197.51)
Lag of MA-term	0.3931*** (4.29)	0.3842*** (4.64)	0.3732*** (4.85)	0.4271*** (6.13)	0.4632*** (7.12)	0.5887*** (12.09)
Constant	1.0001*** (10.17)	0.9964*** (9.67)	0.9994*** (10.27)	1.029*** (13.02)	1.057*** (6.84)	1.1748*** (4.47)
Standard deviation of the white-noise disturbance	0.0064*** (21.45)	0.0060*** (24.08)	0.0058*** (26.74)	0.0059*** (26.54)	0.0062*** (25.76)	0.0077*** (25.40)
Equation in first difference	No	No	No	No	No	No
Number of observations	73	85	97	109	121	133

Notes. t-statistics in brackets. Standard errors are robust to heteroskedasticity with clustering of products. Results marked with one to three stars are statistically significant at 10%, 5% and 1% respectively. The models are run on the price index of electricity corrected by the consumer price index (2005 = 1).

A8. Alternative assumptions for calculating operating costs

1. Different appliance lifetimes

The calculation of the operating costs in the base model is based on AMDEA (2008) information about appliance lifetimes (12.8 years for refrigerators and 17.5 years for combined refrigerators-freezers). Table 19 presents the results where the lifetimes for the two kinds of appliances are assumed to 20% higher and lower. It shows that changes in our assumption have limited impact on the results. This is mostly because operating costs are discounted: electricity consumption in 10-15 years is given a low weight in any case.

Table 19: First difference IV-GMM estimation results of the sales equation, with different appliance lifetimes

Dependent variable: log. market share of product j			
Assumptions on lifetime (years)	Base specification	-20%	+20%
Refrigerators	12.8	10.24	15.36
Combined refrigerators-freezers	17.5	14	21
Independent variables			
Importance of total electricity costs (γ)	0.5671*** (4.32)	0.6587*** (4.33)	0.5059*** (4.31)
Utility for money (α)	0.0052*** (3.51)	0.0052*** (3.51)	0.0052*** (3.52)
Within-group correlation of error term (σ) for the demand equation	0.889*** (16.14)	0.8891*** (16.13)	0.889*** (16.15)
Year dummies	Yes	Yes	Yes
Number of observations	1,365	1,365	1,365

Notes. Two instruments are used. They correspond to the fixed effects capturing year-on-year changes in the price of upright freezers and washing machines. The nests on which σ is calculated distinguish refrigerators from combined refrigerator-freezers, built-in from freestanding appliances, and appliances by capacity (over and below the sample median). *t*-statistics in brackets. Standard errors are robust to heteroskedasticity and clustered on products. Results marked with *, ** and *** are statistically significant at 10%, 5% and 1%, respectively.

2. Alternative assumptions for expected electricity prices

Current prices

Table 20 presents the results of the sales equation with a forecasting model based on the assumption that electricity prices follow a random walk so that the forecasted price at any date $t + s$ is equal to current price at date t. Under this assumption, the underestimation of the operating cost is smaller (10%). It is not surprising as the price of electricity was increasing over most of the study period, implying that ARIMA results underestimate the actual price.

Table 20: First difference IV-GMM estimation results of the sales equation, with contemporaneous electricity price

Dependent variable: log. market share of product j		
Electricity prices	ARIMA model	Current prices
Independent variables		
Importance of total electricity costs (γ)	0.5671*** (4.32)	0.7879*** (3.95)
Utility for money (α)	0.0052*** (3.51)	0.0057*** (3.25)
Within-group correlation of error term (σ) for the demand equation	0.889*** (16.14)	0.863*** (14.04)
Year dummies	Yes	Yes
First difference	Yes	Yes
Observations	1,365	1,365

Notes. Two instruments are used. They correspond to the fixed effects capturing year-on-year changes in the price of upright freezers and washing machines. The nests on which σ is calculated distinguish refrigerators from combined refrigerator-freezers, built-in from freestanding appliances, and appliances by capacity (over and below the sample median). *t*-statistics in brackets. Standard errors are robust to heteroskedasticity and clustered on products. Results marked with *, ** and *** are statistically significant at 10%, 5% and 1%, respectively.

Futures prices

We now compute retail price forecasts using wholesale prices on the UK futures market as a benchmark.

In principle, a rational consumer is likely to form his/her expectations on retail electricity prices in a fashion similar to professional energy traders in the wholesale market. This is because the expectations made by professionals on the wholesale market should approximate a well-informed, rational process of making expectations on the price of electricity. By definition, wholesale electricity futures reflect expectations of professionals about the price of wholesale electricity in the future. Therefore, we exploit this available piece of information on professionals' expectations regarding future prices on the wholesale market to frame the expectations of a rational consumer on the wholesale market.

First, we assume that professionals' expectations are mostly driven by current and previous wholesale electricity prices. This assumption can be confirmed in a model where wholesale electricity futures at time *t* are a function of wholesale spot prices at time *t*, *t*-1, *t*-2 and so on:

$$F_t = F_m + \sum_{s=t-x}^{t} \gamma_s S_s + \varepsilon_t$$

F_t is the futures price at time t, S_s the spot price at time s, F_m is a month-specific constant for month *m* which controls for seasonality, γ_s are coefficients to be estimated and ε_t is an error term. The parameter *x* corresponds to the number of lagged spot prices included in the regression. Empirically, we choose *x* so that all the coefficients γ_s are statistically significant.

Likewise, we consider that a rational consumer would form his expectations about future retail electricity prices based on past prices as his main source of information:

$$q_t^f = q_m + \sum_{s=t-x}^{t} \varphi_s q_s + u_t$$

q_t^f is the forecasted price of electricity for the next periods, q_m a month-specific constant for month m which controls for seasonality, φ_s are coefficients relating current and past prices to price expectations and u_t is an error term.

If rational consumers indeed shape their expectations in strictly the same way as professionals do on wholesale markets, then $\varphi_s = \gamma_s$. We impose this assumption such that we can use the relationship between future and spot wholesale prices to compute retail electricity price expectations with previous and past retail electricity prices. This is because estimating F_t as a function of S_s provides estimates for γ_s, and therefore for φ_s. These estimates are sufficient to derive values for q_t^f based on q_s.

We have collected data on UK wholesale electricity futures from the Bloomberg futures database. More precisely, we use the price of Gregorian baseload forwards from the 1st to the 4th following winter/summer seasons, as registered during OTC operations and gathered by GFI Group Limited. These prices are available on a monthly basis from 2002 to 2007. We calculate an average of the futures prices for the next four seasons and assume that the average corresponds to professionals' expectations (at a specific date) regarding the average price of wholesale electricity during the lifetime of appliances. The data for spot prices of UK Power has been extracted from the reference and settlement data of Bloomberg. Spot prices are used as an independent variable to predict futures. The results of the regression on futures are given in Table 21.

Table 21: Linear regression used to predict monthly futures prices from monthly wholesale electricity prices on the spot market

Dependent variable: UK wholesale electricity futures (2005 pence/kWh)	
Independent variables	
Real wholesale electricity prices on spot market (2005 pence/kWh)	
This month	0.3722** (2.44)
One month ago	0.3744** (2.22)
Two months ago	0.4574** (2.68)
Three months ago	0.3553** (2.29)
By month fixed effects	Yes
Constant	Yes
Observations	69
Adjusted R2	0.79

Notes. Results marked with *, ** and *** are statistically significant at 10%, 5% and 1%, respectively.

The coefficients from the regression above (corresponding to γ_s) are used with observed retail electricity prices to produce estimates of expected retail electricity prices. In mathematical terms, we assume $\varphi_s = \gamma_s$ and $q_m = 0$ to derive q_t^f from q_s.

Once we have computed estimates for q_t^f with this method, we use them to recalculate total actualized and discounted electricity costs and run an alternative GMM regression for the market share equation. The results of the latter regression are provided in Table 22. They show relatively little difference in using expectations based on the futures data with respect to the expected prices obtained with the ARIMA model.

Table 22: First difference IV-GMM estimation results of the sales equation, with expected electricity prices based on UK Power futures

Independent variables	
Importance of total electricity costs (γ)	0.4989*** (4.22)
Utility for money (α)	0.0061*** (3.07)
Within-group correlation of error term (σ) for the demand equation	0.8553*** (12.94)
Year dummies	Yes
Observations	1,365

Notes. Two instruments are used. They correspond to the fixed effects capturing year-on-year changes in the price of upright freezers and washing machines. The nests on which σ is calculated distinguish refrigerators from combined refrigerators-freezers, built-in from freestanding appliances, and appliances by capacity (over and below the sample median). *t*-statistics in brackets. Standard errors are robust to heteroskedasticity and clustered on products. Results marked with *, ** and *** are statistically significant at 10%, 5% and 1%, respectively.

Marginal vs average prices

In the base specification, we use the average electricity price to compute forecasts but this conflicts with the assumption of perfectly rational consumers, who would in theory use marginal price information to form expectations. Unfortunately, data on marginal prices for the study period was not available. As argued in the paper, the results are unbiased if the fixed non-metered component remained constant over the sample period, and biased if not constant. In Table 23, we give results for the sales equation in which a time-varying estimate of the marginal price is used to calculate operating costs.

The marginal price is estimated as follows. According to DECC (2013b), the fixed component corresponds to around 11% of UK electricity bills. We assume that, during the study period, the share remained fixed at 11%.. Under this assumption, Table 23 shows consumer myopia would be smaller, as consumers would underestimate energy costs by 37%.

Table 23: First difference IV-GMM estimation results of the sales equation, where expected electricity prices are estimated using time-varying marginal prices

Independent variables	
Importance of total electricity costs (γ)	0.6371*** (4.32)
Utility for money (α)	0.0052*** (3.51)
Within-group correlation of error term (σ) for the demand equation	0.889*** (16.14)
Year dummies	Yes
First difference	Yes
Observations	1,365

Notes. Two instruments are used. They correspond to the fixed effects capturing year-on-year changes in the price of upright freezers and washing machines. The nests on which σ is calculated distinguish refrigerators from combined refrigerators-freezers, built-in from freestanding appliances, and appliances by capacity (over and below the sample median). *t*-statistics in brackets. Standard errors are robust to heteroskedasticity and clustered on products. Results marked with *, ** and *** are statistically significant at 10%, 5% and 1%, respectively.

A9. Instrumentation of the operating costs to mitigate measurement errors

Several reasons why the operating cost values use in this analysis may be affected by measurement errors have been discussed. Here, we check how such errors potentially impact our results by running a model in which the operating cost is instrumented. We use the lagged electricity prices to compute the operating costs of appliances as if they were functioning during the previous year. Operating costs from the previous year are then used to instrument expected and actualized operating costs. The assumption is that past operating costs are likely to be correlated with expected operating costs, but they should not be correlated with the demand for appliances. This assumption seems reasonable considering that electricity costs have varied significantly over the study period.

Results are given for the sales and price equations. They show little differences with the results obtained in the base specifications.

Table 24: First difference IV-GMM estimation results of the sales equation, with instrumentation of the operating costs

Independent variables	
Importance of total electricity costs (γ)	0.5245*** (3.76)
Utility for money (α)	0.0052*** (3.46)
Within-group correlation of error term (σ) for the demand equation	0.8889*** (16.28)
Year dummies	Yes
Observations	1,365

Notes. Three instruments are used. The first two correspond to the fixed effects capturing year-on-year changes in the price of upright freezers and washing machines. The third instrument corresponds to electricity costs as calculated with one-year lagged electricity prices, since expected electricity costs are endogenous in this setting. The nests on which σ is calculated distinguish refrigerators from combined refrigerator-freezers, built-in from freestanding appliances, and appliances by capacity (over and below the sample median). *t*-statistics in brackets. Standard errors are robust to heteroskedasticity and clustered on products. Results marked with *, ** and *** are statistically significant at 10%, 5% and 1%, respectively.

Table 25: First difference IV estimation results of the price equation, with instrumentation of the operating costs

Independent variables	
Discounted electricity costs, η	-0.4294*** (-2.79)
Year x brand dummies	Yes
Observations	1,365

Notes. The instrument corresponds to electricity costs as calculated with one-year lagged electricity prices, whereas expected electricity costs are endogenous in this setting. *t*-statistics in brackets. Standard errors are robust to heteroskedasticity and clustered on products. Results marked with *, ** and *** are statistically significant at 10%, 5% and 1%, respectively.