The impact of energy prices on energy efficiency: Evidence from the UK refrigerator market

François Cohen, Matthieu Glachant and Magnus Söderberg

CERNA, MINES ParisTech, 60 Boulevard St Michel, 75006 Paris, France

Abstract

It is frequently argued in policy circles that imperfect information and other cognitive constraints may lead consumers to discard privately profitable investments in energy efficiency. Using product-level panel data from 2002 to 2007 on the UK refrigerator market and a discrete-choice framework, we reject this view: our estimate is that purchasers of refrigerators implicitly discount future electricity costs at a reasonably low rate of 10.5%. As consumers apparently make rational investment decisions, taxing energy would be the route to further increase energy efficiency. However, we make simulations which demonstrate a very small elasticity of energy use to the price of electricity (-0.16). The reason is that most of the energy cost increase is compensated by suppliers through relatively larger price reductions of highly energy consuming products. This finding calls for moving attention in the energy efficiency debate to the pricing behavior of manufacturers of durables.

Keywords: Energy efficiency, implicit discount rate, energy price

JEL Codes: D12, L68, Q41.

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1. Introduction

In policy circles, the notion of "energy efficiency gap" is a popular concept which refers to the existence of potentially large differences between the socially optimal and actual level of energy consumption. This gap would create major opportunities for policies to encourage energy savings. As explained by Allcott and Greenstone (2012), it is worth distinguishing between two reasons why public intervention can improve social welfare in this area. The first is the classical externality problem: the production and consumption of energy, in particular of fossil fuels, generate major environmental and health externalities which could be mitigated by policies promoting energy conservation. The second is related to imperfect information and other cognitive constraints which may lead economic agents to discard privately profitable investments limiting energy use, in particular households and SMEs which have limited time and resources to devote to infrequent investment decisions. Allcott and Greenstone (2012) refer to the latter type of market failures as "investment inefficiencies". These inefficiencies particularly fascinate as they mean the existence of win-win options entailing both economic and environmental benefits.

In practice, an investment in energy savings is driven by the comparison of an upfront cost –the purchase of an energy-efficient refrigerator, a fuel efficient car, the installation of insulation – with the streams of future benefits induced by lower energy consumption. The investment choice is inefficient if, in the eyes of an external observer, the decision maker gives too much weight to the upfront cost relative to energy savings benefits. That is, if he or she implicitly uses too high a discount rate. Or, using another terminology, if the decision maker is myopic.

The potential existence of investment inefficiencies has important policy implications. In particular energy taxation or other policy instruments like emissions trading which increase energy prices are likely to have limited impacts on energy use. Accordingly, they constitute a major justification of the numerous real-world policies which target the investment decision such as investment subsidies encouraging the purchase of water heaters or the installation of insulation in dwellings or energy product labelling. They also plead in favor of the use of direct regulation such as quality standards mandating a minimal level of energy or environmental performances of new motor vehicles like the EURO norms in Europe or the US-equivalent CAFE standards, building energy codes, etc.

In this paper, we use product-level panel data from 2002 to 2007 to test the existence of investment inefficiencies in the UK refrigerator market and to estimate the impact of energy taxation on energy use. Refrigerators constitute an interesting case study for they are mostly sold to households which are viewed as more prone to irrational investments than other economic agents. Moreover, in contrast with other durable goods such as cars or air-conditioners, energy consumption is almost entirely determined by the investment decision: Once the refrigerator is purchased, consumers just plug it and consumption is determined by the fridge's characteristics whereas car owners decide how frequently they drive, and thus how much energy they use. This allows deriving more robust results as we do not need critical assumptions on energy use.

By far, this paper is not the first which tries to investigate these issues. Following the work of Hausman (1979) on room air conditioners, many researchers have 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); for air conditioners between 19% to 77% (Matsumoto, 2012; Train and Atherton, 1995; Hausman, 1979; Kooreman, 1995); and for water heaters between 67% and 84% (Hwang et al., 1994; Goett and McFadden, 1982).

We find a much lower discount rate of 10.5%, suggesting limited investment inefficiencies. There are several methodological reasons to believe that our estimate is more accurate than those obtained in previous studies. When seeking to measure the value given by consumers of durables to energy efficiency, the most difficult challenge consists in controlling for other product attributes like design, size, reliability that may be correlated with energy performance. Gately (1980) or Meier and Whittier

(1983) cited above try to solve the problem by comparing a few models of refrigerators that only differ in their energy efficiency level. The problem is that such estimates are based on a non-representative sample. Hedonic pricing models bring more general results by calculating the effect of various product features, including energy efficiency, on the purchase price of domestic appliances. This technique was first used first by Hausman (1979) on room air conditioners and, more recently, by Hwang et al. (1994) and Matsumoto (2012). But these works potentially suffer from serious omitted variables bias as they rely on cross-sectional data with a limited number of control variables of other product attributes. Others have used individual-level information collected in surveys (e.g. McRae, 1985; Revelt and Train, 1998) which, like any stated preference data, are likely to suffer from hypothetical bias. By design, they also restrict the consumers' choice to sets of products that only differ in their energy efficiency level whereas consumers can also purchase smaller appliances to reduce energy costs.

In contrast with previous studies, we rely on first-difference panel data methods which allow controlling for time-invariant unobserved product attributes. We also address endogeneity concerns arising from refrigerators' prices and quantities being simultaneously determined in the market equilibrium. We pay a particular attention to the fact that, contrary to the upfront cost, future benefits are not actually observed, but forecasted by the decision-maker at the time of purchase. In addition, the fact that theoretical modeling does not yield a discount rate which enters linearly in the equation because lifetime is product-specific is also addressed in a GMM framework.

By suggesting limited investment inefficiencies, our finding would thus indicate that energy taxation could be an effective approach to reduce energy consumption. Surprisingly, we run simulations which yield the opposite result as the estimated elasticity is -0.16. That is, a 10% increase in the price of electricity only reduces the average annual electricity consumption of sold appliances by 1.6%.

The reason ultimately lies in the response of the manufacturers and/or retailers to the energy tax. The simulations include two stages: First, we predict the impact of electricity price increase on the refrigerator purchase prices (which is expected to change as energy taxation reduces the demand of less energy-efficient refrigerators). Second, we predict the impact on the purchasing decision. The final impact is very limited because most of the energy costs increase is compensated in the first stage by suppliers which reduce more the purchase prices of high energy consuming models of refrigerators relative to energy efficient ones. Why manufacturers of refrigerators or retailers are able to absorb energy tax shocks by cutting prices is related to the existence of imperfect competition driven by product differentiation in the refrigerator market which leaves them with substantial markups. When assuming that manufacturers or retailers do not adjust prices as it would be the case in a competitive market where prices equal marginal costs, we obtain a four-time higher impact on energy use (the elasticity is -0.58).

We have already explained how our contribution relates to the existing literature on appliances. It is worth mentioning in addition several recent papers which deal with the automobile sector. Sallee et al. (2009) and Allcott and Wozny (2012) are both primarily interested in estimating implicit discount rates and, relying on similar discrete choice models, they also tend to find that the energy efficiency gap is smaller than previously claimed.[1] None of these papers look at the impact of gasoline prices on the price of used or new cars, a mechanism which we show to have major impacts on the effectiveness of energy taxes. In contrast, Busse, Knittel and Zettelmeyer (2009) examine both the level of the discount rate and the price response of car manufacturers and retailers. Interestingly, they show that the price adjustment is much higher in the used car market than in the market for new cars.

[1] There are several reasons why the refrigerators market is simpler to work with compared to the automobile market. First, the second-hand market for refrigerators hardly exists whereas it cannot be ignored in the analysis of the auto market. By the way, Allcott and Wozny only examine the impact of gasoline prices on the second-hand market. Second, refrigerators are much simpler products, and therefore biases associated with time-varying unobservables are likely to be smaller. Finally, the intensity of use for a refrigerator is inelastic to changes in the price of electricity, a point previously made. Their analysis thus requires a critical assumption on the number of miles travelled.

The rest of this paper is structured as follows. In the following section, we develop a discrete choice model to represent consumers' purchasing decision. The model is used to derive a micro-founded econometric specification and to make explicit the simplifying assumptions we need to introduce in order to generate empirical estimates. Section 3 presents the data. We then present and interpret the estimation results. In Section 5, we run simulations to predict the impacts of an increase by 10% in the price of electricity. In Section 6 we summarize the major findings and policy implications.

2. Analytical framework

We adopt the standard discrete choice model for differentiated goods developed by Berry (1994). We consider *T* markets, each representing the UK refrigerator market during year *t* (with *t* = 1,…,*T*). For each such market, we observe aggregate quantities sold, average prices, and product characteristics for *J* models of refrigerators.

Consumers choose the product that maximizes utility. We assume that indirect utility function of consumer *i* who purchases a new refrigerator *j* in year *t* is equal to $U_{i,j,t} = V_{j,t} + \omega_{i,j,t}$ where $V_{j,t}$ is the average utility and $\omega_{i,j,t}$ is consumer *i*'s unobserved heterogeneity which captures deviation from the average. The average utility is:

$$V_{j,t} = u_{j,t} - \alpha \left(p_{j,t} + C_{j,t}(r) \right)$$

In this expression, $u_{j,t}$ captures the value of usage of the refrigerator *j* over its lifetime. $p_{j,t}$ is its purchase price, $C_{j,t}(r)$ is the electricity cost of the product which is forecasted by consumers at the time of purchase. This cost depends on the discount rate r. Later, we will specify the functional form of $C_{j,t}(r)$. α is the marginal utility of money.

Next we decompose the value of usage in two additively separable terms: $u_{j,t} = u_j + \xi_{j,t}$ where $\xi_{j,t}$ captures the time-specific impact of unobserved product characteristics. Hence, we have:

$$V_{j,t} = u_j - \alpha\left(p_{j,t} + C_{j,t}(r)\right) + \xi_{j,t}$$

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

$$s_{j,t} \equiv \frac{e^{V_{j,t}}}{\sum_{k \neq j} e^{V_{k,t}}}$$

A consumer can also choose an outside option indexed 0 which consists in purchasing no refrigerator. Normalizing its utility $V_{i,0,t}$ to zero, the market share of product *j* at time t can be compared with the market share of the outside good so that:

$$\frac{s_{j,t}}{s_{0,t}} = e^{V_{j,t}}$$

In logs, this simplifies to:

$$\ln(s_{j,t}) - \ln(s_{0,t}) = V_{j,t} = u_j - \alpha\left(p_{j,t} + C_{j,t}(r)\right) + \xi_{j,t} \qquad (1)$$

Our final goal is to estimate the discount rate r which influences the electricity cost $C_{j,t}(r)$. Reasoning in continuous time[2] and assuming uniform rates across consumers, we write the electricity cost as follows:

$$C^*_{j,t}(r) = \int_0^{L_j} (q^*_{t+s}\Gamma_j)\mathrm{e}^{-rs} ds \qquad (2)$$

In this equation, L_j is product *j*'s lifetime, $q^*_{j,t+s}$ is the electricity price at time $t+s$ which is forecasted by the consumers and Γ_j is the level of energy consumption per time period.[3] In order to simplify (2), we introduce the assumption that consumers consider an identical expected electricity

[2] In practice, electricity costs are paid in discrete time by consumers. The use of continuous time simplifies calculations with little impacts as the time interval between payments is arguably short compared to the lifetime of refrigerators.

[3] The level of energy consumption is assumed to be constant over time for each refrigerator *j* because the use of cold appliances is inelastic to electricity prices.

price, denoted q_t^*, to all time periods over $[t; t+L_j]$. Under this assumption, the electricity cost becomes:

$$C_{j,t}(r) = \varphi(r, L_j) \cdot q_t^* \cdot \Gamma_j \qquad \text{with} \qquad \varphi(r, L_j) \equiv \left(\frac{1-\exp(-rL_j)}{r}\right) \tag{3}$$

Expectations on future electricity prices

The fact that, contrary to the purchase price, the electricity price is *forecasted* by the consumers when they purchase the refrigerator, the way they form expectations is crucial and may have a key influence on the discount rate. A practical problem is that the expectation for the average electricity price, q_t^* is not observed. A solution would be to proxy q_t^* with q_t, the actual market average electricity price. But this would introduce a measurement error which would potentially bias the coefficient.

To proxy price expectations, we follow Popp (2002) by adopting an adaptive expectation framework. It is assumed that consumers adapt to electricity price changes by paying attention to the relative yearly increase of real electricity prices. Specifically, let $\theta_t \equiv q_{t+1}/q_t$ denote the relative yearly increase of real electricity prices and θ_t^*, the increase which is expected. The adaptive model assumes the following relationship:[4]

$$\theta_t^* = \theta_{t-1}^* + \lambda(\theta_{t-1} - \theta_{t-1}^*) \tag{4}$$

Eq. (4) means that current expectations θ_t^* are composed of past expectations and an "error adjustment" term, which raises or lowers the expectations depending on the realized value of θ_t. Parameter $\lambda \in (0,1)$ captures the adjustment speed between past and current expectations.

[4] The later means that consumers would have in mind year-to-year changes in relative terms (e.g. increase by 10% last year and by 5% the year before) and form expectations based on these relative price increases. The choice of a relative yearly increase of real electricity prices to construct adaptive expectations, instead of other variables, such as the year-to-year value of the electricity prices or the absolute difference in real prices from one year to another, was mainly driven by the empirical conclusion that expected prices with this calculation method were a better predictor of future prices. We therefore considered that rational consumers were more likely to use such a method to get more accurate estimates of future electricity prices.

Applying Eq. (4) recurrently over all past periods, expectations at time t of the price increase for t + 1 are a weighted sum of past expectations:

$$\theta_t^* = \lambda \sum_{k=0} (1-\lambda)^k \, \theta_{t-\mathrm{k}-1}^{\mathrm{k}+1}$$

We choose the value of λ which minimizes the square of the difference between expected price increases θ_t^* and observed price increases θ_t. The precise method is described in the data section. Once a value of λ is estimated, the adaptive adaptation framework allows us to calculate consumers' expectation at time t about electricity prices at time t + 1:

$$q_t^* = q_t \sum_{k=0} (1-\lambda)^k \left(\frac{q_{t-\mathrm{k}}}{q_{t-k-1}}\right)^{\mathrm{k}+1} \tag{5}$$

Econometric specification

We now transform Eq. (1) into a specification that can be estimated econometrically. To do so, we first substitute (3) in (1). Next we add year dummies τ_t and we substitute all variables by their first-differences in order to absorb the share of the outside option, the value of usage and any shift in the overall market share level. This leads to:

$$\Delta \ln(s_{j,t}) = -\alpha \left(\Delta p_{j,t} + \left(\frac{1-\exp(-rL_j)}{r}\right) \cdot \Delta q_t^* \cdot \Gamma_j \right) + \Delta\tau_t + \Delta\xi_{j,t} \tag{6}$$

where $\xi_{j,t}$ is now the econometric error term capturing unobserved time- and product-varying heterogeneity and Δ represents the first-difference.

Estimating (6) is not necessarily straightforward as the equation is non-linear in the variables L_j, Δq_t^*, and Γ_j. The standard approach used in most papers consists in assuming a uniform lifetime: $L_j = L$ where L is the market average lifetime. In this case, (6) becomes linear and standard linear models apply. The implicit discount rate is then derived by solving for r the following equation:

$$\varphi = \left(\frac{1 - \exp(-rL)}{r}\right)$$

A further reason to opt for this solution is that product-specific information on lifetimes is generally not available. The problem with this assumption is that it is very restrictive as products typically exhibit different levels of durability. In our case, the lifetime is 12.8 years for refrigerators and 17.5 years for combined refrigerators-freezers (AMDEA 2008). As the discount rate and the lifetime are tightly linked in the operating cost formula (3), a measurement error in the lifetime variable mechanically introduces a bias in the estimates of *r*.

This leads us to estimate (6) with a non-linear GMM estimator. Nevertheless, in the Appendix we include the results obtained with the linear approach as a test of robustness. As we will see, assuming a uniform lifetime tends to underestimate the value of *r* although the estimates with the linear model are not significantly different compared to the GMM results.

A further econometric issue is that the purchase price $p_{j,t}$ is endogenous as quantities and prices are simultaneously determined in market equilibrium. This leads unobserved product characteristics to be correlated with prices, i.e $E[p\xi] \neq 0$. An instrumental variable approach is thus adopted.

To construct the instruments, we take advantage of the fact that the market is imperfectly competitive. It follows that characteristics of products $k \neq j$ such as price or energy consumption influence $p_{j,t}$, but not the utility $V_{j,t}$. Berry (1994) suggests to construct relevant product groups and use the averages for different product features within and/or out of the product group that product *j* belongs to as instruments. In our case, we use the within-group averages as they prove to be more powerful instruments. Formally, the instruments $\mathrm{Z}_{j,t}$ are given by:

$$\mathrm{Z}_{j,t} = \sum_{\mathrm{k} \in B_{g(j),t}} \frac{X_{k,t}}{N(B_{h(j),t})}$$

where $X_{j,t}$ is an observable product characteristic and $N(B_{h(j),t})$ is the number of refrigerators in group *h* that includes product *j* at time *t*. We use three product attributes to construct three instruments that are used to estimate the non-linear model with GMM: appliance price, total capacity (including freezing and refrigerating capacities) and energy efficiency rating. The groups are defined using two variables: the built-in/freestanding feature and product size categories.[5,6]

3. Data

We use market data from the refrigerator market in the UK on the product level from 2002 to 2007 collected by *GfK Retail and Technology* and made available by the Department for Environment, Food and Rural Affairs. The data includes detailed information on refrigerators and combined refrigerators-freezers sold in the UK during that period. We identify products by relying 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 availability of freezer), and, when available, on brand name and series numbers.[7]

Each observation is a product *j* in year *t* of which we know the number of units sold, the average consumer price, a set of product features such as the size, whether it is a simple refrigerator or a refrigerator-freezer, which have a separate freezing compartment that can store food at -18°C, and annual electricity consumption (see details in Table 1).

Importantly for our study, we also know the product's classification according to the EU energy rating label. Energy labeling is mandatory since 1995 for all refrigerators sold in the European Union. In our

[5] Five size categories were constructed based on the quintiles of total appliance capacity (in litres) as registered in the data.

[6] To determine the most relevant product groups, we use the OLS estimator with constant lifetimes (results in the Appendix). This is because tests of weak instruments are available for linear models whereas they are not available for the GMM estimator. The test results and a sensitiveness analysis are available in Appendix.

[7] In particular, exact brand name and series numbers were not available for retailers' 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, making impossible to follow them up between 2002 and 2007. On the other hand, for the products for which brand name and series numbers are available, identification on product features is always necessary considering that manufacturers can change some of the product features of a model without changing the series number (there can be various versions of a same model of appliance).

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 in comparison with products providing the same cooling services.

We do not have detailed information on product-specific lifetime. We use the information provided by the Association of Manufacturers of Domestic Appliances which estimates that the lifetime is 12.8 years for refrigerators and 17.5 years for combined refrigerators-freezers (AMDEA 2008). In the linear case with homogeneous lifetimes (which has been used for controlling the strength of the instruments), we use 15.62 years which is a weighted average of these two figures where weights reflect the market shares of these two types in our data over the period 2002-2007.

Moreover, we have dropped products with low sales. The observations with 10 units sold units or less were dropped as well as all the observations of a given product if the product was never sold more than 250 units in one year.[8]

Summary statistics on product characteristics are displayed in Table 1. The initial data set includes 3,231 observations, of which 2,315 are used to construct the first differences for the econometric estimation. The total number of differences used in the econometric estimation is thus 1,413. Descriptive statistics are provided for the 2,315 observations used to construct the differences of the final estimation sample. Besides, Table 2 provides an overview of the distribution of prices and market shares across energy efficiency classes and size categories.[9]

[8] By removing the first type of outliers, the goal is to avoid having models with sales near zero, creating a bias for estimating the discrete choice model. Dropping the second type ensures that models in the sample were actually commercialized at a large scale (not only on a few local markets) at least during one year over the period.

[9] To circumvent the problem of missing observations we calculating the differences over the shortest time interval, for example, between year *t* and year *t*-2, or between year *t* and year *t*-3.

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	2657	5454
Purchase price, $p_{j,t}$	real £	370	260
Appliance lifetime, L_j	years	15.41	2.34
Energy consumption, Γ_j	kWh/year	319	143
Height	cm	140	42
Width	cm	59	9
Capacity	litres	246	112
Energy efficiency rating[a]		2.50	0.89
Share of combined refrigerators-freezers		0.56	-
Share of built-in appliances		0.20	-
Share of appliances with no-frost system		0.23	-
Instrumental variables, $Z_{j,t}$			
Within-group: price		408	226
Within-group: energy efficiency rating		2.58	0.46
Within-group: capacity		249	109

Notes. Source: GfK, made available by Defra. Survey years: 2002-2007. 2,315 observations. The values for the instrumental variables are calculated over the entire set of appliances in the data, in particular before outliers with too few sales are dropped, and also with appliances only appearing one year (that could not be included in the regressions). [a] To obtain a numeric value with the energy efficiency rating (from “G” to “A++” for the 2002-2007 period), ratings were recoded. “A++” was recoded as 0, “A+” as 1, “A” as 2 and so on up to 8 (for “G”).

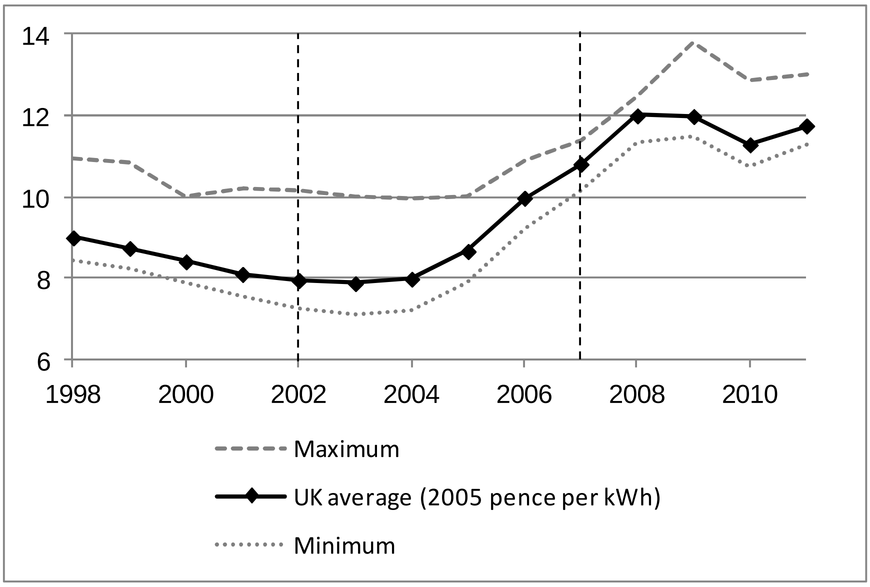
Table 2: Sales-weighted price and market share of appliances, breakdowns by energy efficiency class and size

Category	Sales-weighted average price	Market share
Energy efficiency rating		
A++	335	0.03%
A+	275	2.01%
A	309	62.79%
B	225	21.85%
C	238	12.94%
D	108	0.26%
G	135	0.12%
Size		
First quintile[a]	162	29.69%
Second	232	20.61%
Third	290	26.60%
Fourth	354	14.55%
Fifth	649	8.55%

Notes. Source: GfK, made available by Defra. Survey years: 2002-2007. 2,322 observations. No observation with energy efficiency rating of “E” or “F”. [a]The first quintile includes the smallest appliances.

We obtain data on retail electricity price from the Department of Energy and Climate Change (2013). The electricity price data includes average unit prices (in £/kWh) for 15 selected towns and cities for 1998-2011.[10] The price of electricity is displayed for three modes of payment (credit, direct debit, prepayment), which we average to obtain only one value for each year at national level that is used to calculate the expected electricity price. As shown in Figure 1, our study covers a period during which a major change occurred in the UK electricity market: after a long period of decrease, retail electricity prices started increasing in 2004. This shift leads us to think that consumers' expectations about future electricity prices may be different from the electricity price at the year of purchase.

Figure 1: Evolution of the average retail electricity price in the UK, along with minimum and maximum average prices recorded at local level (the study period is indicated)



Source: own calculations based on monthly data from UK Office for National Statistics on retail prices index and Department of Energy and Climate Change (2013)

[10] These are Aberdeen, Belfast, Birmingham, Canterbury, Cardiff, Edinburgh, Ipswich, Leeds, Liverpool, London, Manchester, Newcastle, Nottingham, Plymouth and Southampton. Note that the UK average p is not an average for

Additionally to national averages, the electricity price data includes average unit prices (in £/kWh) for 15 selected towns and cities for 1998-2011.[11] We use this more disaggregate data to estimate the value of λ, necessary to model electricity price expectations (see Eq. (5)). More precisely, λ is calculated by minimizing the square of the difference between expected price increases $\theta^*_{k,t}$ in city *k* with observed annual electricity price increases $\theta_{k,t}$ over 1998-2011, using a non-linear least square estimation method:

$$\hat{\lambda} = \arg\min_{\lambda} \sum_{\mathrm{k}} \sum_{t=1}^{\mathrm{n}} (\theta^*_{k,t-1} - \theta_{k,t-1})^2$$

Using city-level data makes the estimation of λ more precise than if it was estimated on national prices. We obtain a value of $\hat{\lambda}$~0.84 (see table 3 below).

Table 3: Non-linear least square estimation of adjustment speed parameter

Dependent variable	Yearly local price increase
Adjustment speed (λ)	0.8444*** (11.43)
Observations	150

Notes. t-statistics in brackets. Standard error is clustered on towns and cities. Results marked with one to three stars are statistically significant at 10%, 5% and 1% respectively. The value of λ has been calculated using 3 lags for $\theta_{i,t}$. A correction is brought to equation (5) to ensure a correct estimation of λ with a finite number of lags.

[11] These are Aberdeen, Belfast, Birmingham, Canterbury, Cardiff, Edinburgh, Ipswich, Leeds, Liverpool, London, Manchester, Newcastle, Nottingham, Plymouth and Southampton. Note that the UK average p is not an average for

4. Results

Estimation results for the base specification are shown in Table 4. We find a statically significant implicit discount rate of 10.5% with a 95% confidence interval of 2.8%-18.0%. This estimate is significantly lower than the implicit discount rates reported in previous research. It also sounds quite close to actual financial interest rates. For instance, the average nominal credit card interest rate was 15.76% for 2002-2007 according to the Bank of England (2013, indicator code is IUMCCTL).

This result is robust to changes in the parameters used to calibrate the GMM model: the sensitiveness analysis with different values for product lifetimes, samples and electricity prices presented in appendix show little differences in the magnitude of the implicit discount rate.

Table 4: First difference GMM estimation results

Dependent variable	Log market share of product *j*
Utility for money (α)	0.0163*** (2.65)
Implicit discount rate (r)	0.1045*** (2.69)
Year dummies	Yes
Observations	1,419
Test of over-identifying restriction	Hansen's J chi2(4) = 3.89 (p = 0.42)

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

A reason for the inexistence of investment inefficiencies might be due to the fact that there actually exists a policy targeting purchase decisions: Energy labeling is mandatory for refrigerators in the European Union. Our result could thus indicate that this information-based approach was able to mitigate potential inefficiencies in the UK market. 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 low discount rate can also indicate the existence of environmentally-friendly consumers who take energy externalities into account in their purchasing decision.

5. A simulation of electricity price increase

If further reductions in energy consumption is a policy objective for domestic appliances – and there are many reasons to believe that it should be[12] – our low implicit discount rate suggest that increasing the electricity price is the route to follow. In this section, we investigate this scenario by running simulations. More precisely, we simulate the effect that a 10% increase in the price of electricity in 2002 would have had on the sales of energy efficient refrigerators and refrigerators-freezers between 2002 and 2007 and on the overall level of annual energy consumption of sold appliances.

To make such a simulation, we need to make 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.[13] This is not unrealistic since purchases of refrigerators are mostly replacements and that households are unlikely to do without a 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 short-term effect is not taken into account in the simulation. Second, it is assumed that the electricity price increase does not change the set of products available on the market. This assumption is uncontroversial in the short run, but could be questioned in the long run, because additional incentives for energy efficiency could encourage producers to launch new energy-efficient products in the market. Third, our specification uses the expected electricity prices, not the real price. In order to calculate the impact of the price increase, we assume that expected electricity prices would rise proportionally with real electricity prices (hence, by 10%).

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[12] 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 its course to achieve only half of his objective (European Commission, 2011a).

[13] Our model cannot predict the evolution of the market share of the outside good under a 10% increase in the price of electricity and, therefore, it is not possible to determine how the total amount of sold appliances would evolve.

The most crucial issue is how we deal with the fact that increasing electricity price influences the market price of refrigerators (which translates in econometric terms by the endogeneity of the price variable in (6)). The point is that producers will respond to power price increase by decreasing the purchase price as higher cost of use reduces the demand for refrigerators. One can even anticipate an asymmetric response: they will reduce more the price of high energy-consuming products relative to that of energy–efficient products.

We thus need to predict the impact on product *j's* purchase price $p_{j,t}$ to properly simulate the final impact of taxation on consumers' behavior. We do so very simply by estimating a price equation in which the regressors are the lifetime electricity costs discounted at the rate estimated in the previous section and the instruments. In fact, we mimic the first stage results that are obtained in a standard two-stage least squares. Results are provided in Table 5. The coefficient for discounted lifetime electricity costs is very high: it says that 72% of the increase in electricity costs is compensated by the manufacturers through a decrease in purchase prices. One can thus anticipate limited impacts on energy use.

Table 5: Results for the purchase price equation (first- difference GMM estimator)

Dependent variable	Purchase price
Discounted lifetime electricity costs with r=0.1045	-0.7267*** (-3.71)
Instruments	
Within-group: energy efficiency rating	-49.39** (-2.53)
Within-group: price	0.34*** (4.63)
Within-group: appliance capacity	-1.30* (-1.65)
Year dummies	Yes
Observations	1,413

Notes. t-statistics in brackets. Standard errors robust to heteroskedasticity with clustering of products. Results marked with one to three stars are statistically significant at 10%, 5% and 1% respectively.

We then simulate the impact of the price increase as follows. First, we use the above appliance price equation to predict the impact of the electricity price increase on $p_{j,t}$. Second, we use the estimates of the sales equation (Table 4) to predict product *j*'s sales $s_{j,t}$. 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 both in a baseline scenario (with historical prices) and in a scenario with a 10% increase in the price of electricity.

Results are displayed in Table 6. It shows that energy consumption of purchased appliances is not substantially modified: we estimate an elasticity of energy consumption to an increase in the electricity price equal to -0.16.

Table 5: Simulated impacts on average purchase price, electricity cost, and annual energy consumption of a 10% increase of the electricity price.

Sales-weighted averages	Baseline	Electricity price 10% higher	Net impacts
Average purchase price (A)	£ 285.21	£ 264.79	-20.42 (-7.2%)
Average lifetime electricity cost (B)	£ 223.15	£ 241.05	17.9 (8%)
Average total net present costs (A+B)	£ 508.36	£ 505.84	-2.51 (-0.5%)
Average energy consumption (kWh/year)	319.48	314.28	-5.2 (-1.6%)

Notes. Based on the results of model (1). Relative changes in brackets in third column.

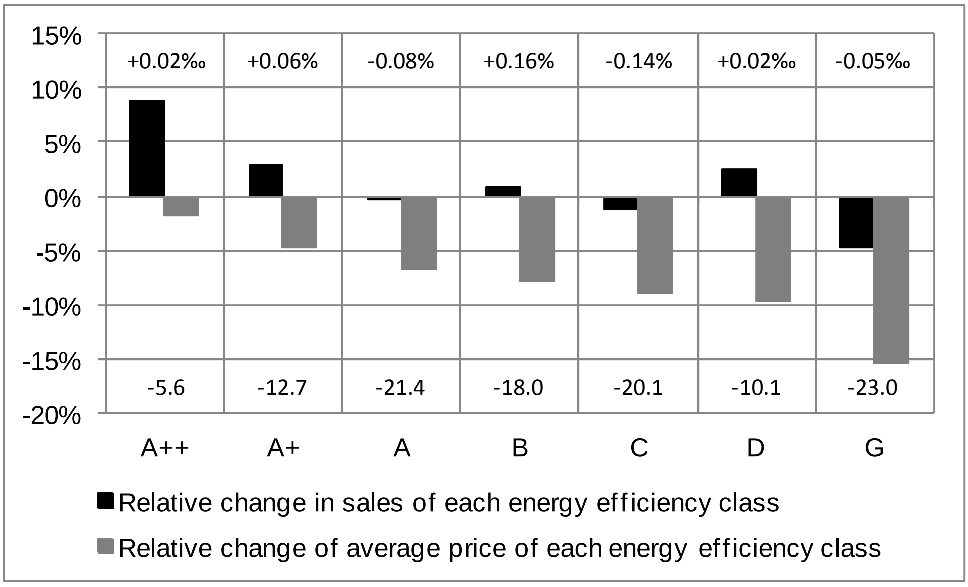
In order to interpret that result, note first that the increase of electricity costs (B in Table 6) is partly compensated by retailers and producers through a decrease in the purchase price of appliances (A in Table 6). As consumers opt for smaller appliances and that appliances are sold at a lower price, the total discounted costs of purchasing and running the appliances even slightly decrease (-0.5%).[14]

Nevertheless, although the average impact on total cost is low, one could imagine heterogeneous impacts across product groups which would induce a re-allocation of market shares in favor of less energy-consuming products, and thereby a significant effect on overall energy use. This does not

[14] This does not mean that the increase of the electricity price improve consumers' utility as the average utility of owning the purchased appliances also decreases.

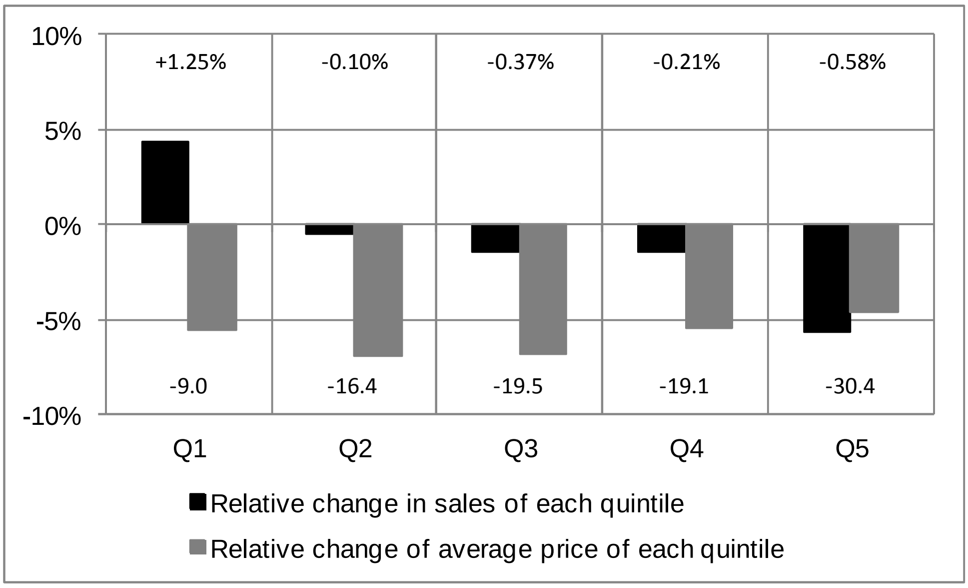
occur because, as anticipated, the price response of manufacturers and retailers is asymmetric. This is visible in Figure 3 which displays the simulation results with a breakdown by energy efficiency class. Demand shifts from energy consuming to energy efficient appliances to a limited extent because suppliers compensate the higher increase of the electricity costs of less efficient products by decreasing their purchase price more. The same pattern is observed when comparing decreases of sales for small and large appliances, as shown in Figure 4.

Figure 3: Simulated impacts of the 10% price increase of electricity by energy efficiency class



Note: The values displayed above the bars correspond to the absolute shift in market shares, and the values displayed below the bars to the absolute change in the sales-weighted average price of each category.

Figure 4: Simulated impacts of the 10% price increase of electricity by quintile of capacity



Note: the values displayed above the bars correspond to the absolute shift in market shares, and the values displayed below the bars to the absolute change in the sales-weighted average price of each category.

These results convey an important policy message. Even if consumers correctly value the future cost of energy consumption when they purchase appliance, taxing energy might have limited impacts in markets for domestic appliances because suppliers are able to cushion the impact of electricity price shocks by asymmetrically reducing purchase prices. This supply-driven "rebound effect" is made possible by the fact that the market is imperfectly competitive due to product quality differentiation. In a competitive market where the price equals the marginal cost of production, producers have less latitude in their pricing strategies.

If we assume that the marginal production cost is constant –a hypothesis which does not sound heroic–, the producers would keep the same prices after the tax reform. Table 6 gives the results of a new simulation in which we assume no change in the price of each appliance *j*. Under this scenario of perfect competition, the elasticity of the energy consumption of purchased appliances to an increase in the electricity price would be -0.58, which is almost four times more than in the first simulation.

Table 6: Simulated impacts on average purchase price, electricity cost, and annual energy consumption of a 10% increase of the electricity price, assuming no change in purchase price (perfect competition)

Sales-weighted averages	Baseline	Electricity price 10% higher no price adjustments$	Net impacts
Average purchase price (A)	£ 285.21	£ 269.50	-15.71 (-5.5%)
Average lifetime electricity cost (B)	£ 223.15	£ 229.70	6.55 (2.9%)
Average total net present costs (A+B)	£ 508.36	£ 499.21	-9.15 (-1.8%)
Average energy consumption (kWh/year)	319.48	300.94	-18.54 (-5.8%)
Average capacity (liters)	237.00	225.15	-11.84 (-5%)

Notes. Based on the result of model (1). In this simulation, the price of each appliance j is assumed to remain unchanged as a result of a VAT increase. Relative changes in brackets in third column. $: Even though the price of each unit remains constant between this scenario and the baseline scenario (VAT 5%), the sales-weighted average price evolves due to changes in the composition of sales.

It is then interesting to compare the size of the inelasticity resulting from imperfect competition from that induced by too high a discount rate. To do so, we run an additional simulation in which the implicit discount rate is assumed to be much lower, and compare the results with the previous simulations. For the new value of the implicit discount rate, we select one of the lowest interest rates available to households and reported by the Bank of England: the average real interest rate to households for a 2-year fixed mortgage with a 75% loan-to-value ratio. The average nominal rate of this type of loans was 5.02% in the UK for 2002-2007. Once deflated, it corresponds to a real interest rate of 3.24%.[15] Using such a low implicit discount rate ensures that our simulation will capture all the potential benefits of reducing the information gap that could lead consumers to underestimate energy savings.

Note that it is possible to simulate new sale and price levels both in the baseline and the policy scenarios with a low implicit discount rate of 3.24%. However, to make comparisons easier, we do not change the sale and price levels of the baseline scenario. We do as if they corresponded to the

[15] The source of the nominal interest rate is Bank of England (2013). The code of the indicator is IUMBV34. The inflation rate used to deflate the interest rate is a 2002-2007 average of the inflation rate of UK consumers' price index (Office for National Statistics, 2013).

market equilibrium with a low implicit discount rate of 3.24%. We then calculate the impact of transiting from the levels of the baseline scenario to a new equilibrium with a 10% increase in the price of electricity. To reach this new equilibrium, the implicit discount rate applied by consumers to any increase of in lifetime electricity costs is 3.24%. This allows us to directly compare the results of this extra simulation with the previous ones. Importantly, we let suppliers adapt products' prices to the shock on electricity prices.

Table 7: Simulated impacts on average purchase price, electricity cost, and annual energy consumption of a 10% increase of the electricity price, assuming an implicit discount rate of 3.24%

Sales-weighted averages	Baseline (with implicit discount rate of 3.24%)	Electricity price 10% higher (with implicit discount rate of 3.24%)	Net impacts
Average purchase price (A)	£ 285.21	£ 252.01	-33.2 (-11.6%)
Average lifetime electricity cost (B)	£ 362.41	£ 385.18	22.78 (6.3%)
Average total net present costs (A+B)	£ 647.62	£ 637.19	-10.43 (-1.6%)
Average energy consumption (kWh/year)	319.48	310.47	-9.01 (-2.8%)
Average capacity (liters)	237.00	231.18	-5.82 (-2.5%)

Notes. Based on the result of model (1). In this simulation, the implicit discount rate applied to operating costs is 3.24%. In the baseline scenario, this is assumed to have no impact on sales and prices, even though operating costs are higher than in the previous simulations. However, this increases consumers' sensitiveness and suppliers' response to the electricity price increase in the policy scenario. Relative changes in brackets in third column.

In this last simulation, the 10% increase in electricity prices would have reduced the annual energy consumption of sold appliances by 2.8%. This is relatively close to the result obtained with the estimated implicit discount rate of 10.8% (reduced energy consumption of 1.6%). On the opposite, the reduction in the annual energy consumption of sold appliances would be much sharper under perfect competition (minus 5.6%, even assuming a higher implicit discount rate of 10.8%). Therefore, according to our simulations, this is clearly imperfect competition, and not any underestimation of the energy savings resulting from the purchase of energy efficient appliances, that explains the inelasticity of the energy consumption of sold appliances to an increase in price of electricity.

However, an important limitation of this analysis is the assumption that decreasing appliance prices is the only option available to manufacturers to adapt to shocks in the price of electricity. In practice, they could also innovate and launch new products consuming less electricity as mentioned previously. Allowing for this alternative strategy is not tractable in our framework, but it would alleviate the effect of suppliers' response on the annual electricity consumption of sold appliances.

6. Conclusion

The literature suggests that consumers' implicit discount rates for cold appliances are suspiciously high. By using a discrete choice model on UK market-level panel data to estimate consumers' valuation of energy savings, we find an implicit discount rate of 10.5%, which is substantially lower than previous estimates. This result is robust to many factors, in particular the average lifetime of appliances, expected energy prices and sampling choices. Contrary to previous works on appliances, our model controls for unobserved product characteristics with product-specific fixed effects and we directly estimates the implicit discount rate by specifying the function of expected lifetime running costs. Evidence that the energy efficiency gap could be much lower than previously thought has been found with similar methodologies applied to the US automobile market (Sallee, West and Fan, 2011; Allcott and Wozny, 2012).

From a policy perspective this result suggests that the EU energy label policy, which provides consumers with information on the energy performance of appliances, has been able to mitigate investment inefficiencies. The fact that consumers rationally respond to price signals could also plead for energy taxation if further energy savings is sought. However, our simulations identify another market failure which erodes the effectiveness of the energy price-based approach: as competition in the refrigerators market is imperfect, manufacturers and retailers are able to partly absorb electricity price shocks, by cutting the purchase price of least energy-efficient appliances more. As an illustration, we estimate that a 10% increase in the price of electricity induces a limited 1.6%

decrease in the average electricity consumption of sold appliance. Note that we may underestimate the impact on energy use as we do not endogenize product innovation. That is, the fact that, in response to electricity price shocks, manufactures can launch new products, thereby modifying the portfolio of products for sale.

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Appendix

A1 - Linear specification with uniform lifetimes

As mentioned previously, a standard approach in previous works consists in assuming uniform lifetimes so that φ becomes a parameter and the equation can be estimated using a usual 2SLS estimator. Running this regression has two objectives: 1) to check the robustness of our results and 2) to run three tests to control that the instruments used in our base model are strong. In this way, we complement the information provided by the test of over-identifying restrictions run for the non-linear model, which ensures that our base model is not over-identified.

The results are presented in Table A1 with a uniform lifetime of 15.62 years which corresponds to the market average. The coefficients for the purchase price and electricity costs are negative and statistically significant at 1%. They imply that a representative consumer would be indifferent between a £ 1 decrease in lifetime electricity costs and a decrease of the purchase price of the appliance by £ 0.64[16]. The corresponding implicit discount rate is 6.3%, which is far below the implicit discount rates reported in previous research. But it remains in the confidence interval of the discount rate estimated with the non-linear model. In addition, results show that the instruments exhibit the necessary properties as they pass all three tests (an under-identification test, a weak identification

[16] This corresponds to the ratio between α and φ.

test and an over-identification test)[17]. In particular, the value for the Kleibergen-Paap rk Wald F statistic ensures that the instruments chosen to run the base model are strong.

Table A1: Linear IV regression assuming a uniform lifetime of 15.62 years

Linear model	Main equation	Endogenous variable
Dependent variable	Log market share of model *j*	Price
Price	-0.0229*** (-3.03)	
Lifetime electricity costs	-0.0145*** (-2.84)	-0.53*** (-2.87)
Instruments		
Within-group: energy efficiency rating		-63** (-2.16)
Within-group: price		0.30*** (3.75)
Within-group: appliance capacity		-1.56 (-1.40)
Year dummies	Yes	Yes
Observations (in first difference)	1,413	1,413
Underidentification test		
Kleibergen-Paap rk LM statistic	13.7 (p = 0.0033)	
Overidentification test		
Hansen J statistic – P-value should be over 5%	0.08 (p = 0.96)	
Kleibergen-Paap rk Wald F statistic	7.159 [a]	

Notes. T-statistics in brackets. Estimates efficient for homoskedasticity only. The limited information maximum likelihood (LIML) is used. Standard errors robust to heteroskedasticity with clustering of products. Results marked with one to three stars are statistically significant at 10%, 5% and 1% respectively. Year 2002 is used as reference for the year dummies. [a] According to the Stock-Yogo (2005) weak ID test critical values, this indicates less than 10% LIML size bias.

A2 – Different sampling rules

In Table A2, we explore the impact of different sampling rules on the estimated discount rates. As explained previously, we have removed outliers from the sample, and more specifically observations with very low sales. Table A2 proposes variants where the rules are used to removing outliers from

[17] Note that there exist 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 into account heteroskedasticity, provides a result above the critical value for 5% maximal IV relative bias. Furthermore, the IV regression was run assuming homoskedasticity and instruments passed all three tests (underidentification, weak identification and overidentification).

the estimation sample. It shows limited impacts on the estimated discount rate and the coefficient remains statistically significant.

Table A2: Estimation results table of sensitiveness analysis over sampling

	Base model	(1)	(2)	(3)	(4)	(5)
Assumptions on sampling						
Annual sales (units)	>10	>10	>50	>100	>10	>10
Sales level of product at least once over the period (units)	>250				>100	>500
Log. Market share of product j						
Utility for money (α)	0.0163*** (2.65)	0.0113** (2.52)	0.0113** (2.05)	0.0079 (1.39)	0.0173*** (2.65)	0.0134** (2.08)
Implicit discount rate (r)	0.1045*** (2.69)	0.0948** (2.40)	0.1250*** (2.62)	0.1288** (2.21)	0.08*** (2.72)	0.0682* (1.88)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1,413	1,993	1,419	1,160	1,734	1,139

Notes. t-statistics in brackets. SEs robust to heteroskedasticity with clustering of products. Results marked with one to three stars are statistically significant at 10%, 5% and 1% respectively.

A3 – Different assumptions for electricity prices

In the base model, expected electricity prices at $t + 1$ are computed based on the assumption that consumers make adaptive expectations. Alternatively in the model below, we assume that consumers make their decision based on the actual electricity price at time t. The results are very different as the implicit discount rate found with model (6) is 4.0% and not statistically significant. This is not surprising: it means that consumers were anticipating electricity price increases during the 2002-2007 period, as modeled through adaptive expectations.

Table A3: Summary table of sensitiveness analysis over electricity price expectations

	Base model	(6)
Assumptions on electricity price expectations	Adaptive expectations	Future price = Current price
Log. Market share of Product j		
Utility for money (α)	0.0163*** (2.65)	0.0157*** (2.65)
Implicit discount rate (r)	0.1045*** (2.69)	0.0400 (1.38)
Year dummies	Yes	Yes
Number of observations	1,413	1,413

Notes. t-statistics in brackets. SEs robust to heteroskedasticity with clustering of products. Results marked with one to three stars are statistically significant at 10%, 5% and 1% respectively.

A4 – Different assumptions for 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 A4 presents the results of alternative models, in which the lifetimes for the two kinds of appliances are assumed to 20% higher or lower. It shows that changes in our assumption have limited impact on the implicit discount rate. This is mostly because operating costs are discounted: electricity consumption in 10-15 years is given small importance in any case.

Table A4: Summary table of sensitiveness analysis over lifetime of appliances

Model Fixed-effect IV regression	Base model	(7)	(8)
Assumptions on lifetime (years)	AMDEA (2008)	-20%	+20%
Refrigerators	12.8	10.24	15.36
Combined refrigerators-freezers	17.5	14	21
Log. Market share of product j			
Utility for money (α)	0.0163*** (2.65)	0.0166 *** (2.66)	0.0162*** (2.64)
Implicit discount rate (r)	0.1045*** (2.69)	0.0911** (2.13)	0.1113*** (3.05)
Year dummies	Yes	Yes	Yes
Number of observations	1,413	1,413	1,413

Notes. t-statistics in brackets. SEs robust to heteroskedasticity with clustering of products. Results marked with one to three stars are statistically significant at 10%, 5% and 1% respectively.