Consumer Myopia, Imperfect Competition and the Energy Efficiency Gap: Evidence from the UK Refrigerator Market

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Abstract

The empirical literature on the energy efficiency gap concentrates on demand inefficiencies in the energy-using durables markets and finds evidence that consumers underestimate future energy costs when purchasing a new appliance. We take a broader view and also consider the impact of imperfect competition. Using data on the UK refrigerator market (2002-2007), we find that the average energy consumption of appliances sold during this period was only 7.2% higher than what would have been observed under a scenario with a perfectly competitive market and non-myopic consumers. One reason for this small gap is that market power actually reduces energy use.

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

JEL Classification: D12, L68, Q41.

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1. Introduction

In energy and environmental policy circles, it is commonly believed that an "energy efficiency gap" exists between the desirable level of energy consumption and observed consumption (e.g. IEA 2007, Ryan et al. 2011). Since the seminal paper by Hausman (1979) and the discussion of possible policy implications by Jaffe and Stavins (1994), the energy efficiency gap has also attracted considerable interest in the academic literature (see the literature survey by Gillingham and Palmer 2014).

To clarify the notion, it is necessary to distinguish two reasons that drive the gap between the actual and socially optimal levels of energy consumption. The first is the classic 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 energy efficiency gap refers to a second category of failures in the markets of energy-using durables. Energy efficiency outcomes involve decisions whereby consumers first make an upfront investment in durable goods and then consume energy through their use. Examples include water heaters, building insulation, motor vehicles and household appliances. The idea of the gap is rooted in a widespread belief that the market for energy-using durables does not operate effectively, i.e. markets are not perfectly competitive with fully rational economic agents. As a result, the market equilibrium maintains an energy efficiency gap defined as a wedge between the cost-minimizing level of energy efficiency and the level actually reached.

Policy discussions, as well as the academic literature, focus on the demand-side of the markets (IEA, 2007; Ryan et al., 2011; Allcott and Greenstone, 2012; Gillingham and Palmer, 2014). The key concern here is that imperfect information and other cognitive constraints could lead consumers to discard privately profitable investments.[1] More specifically, it is often asserted that consumers are myopic in the sense that they give too much weight to the upfront cost or, expressed differently, the discount rate implicitly used to calculate the net present value of the investment is too high. As a result, consumers use too much energy.

This is only half of the picture, however. On the supply side, manufacturers of energy-using durables also make decisions. In particular, they choose product characteristics and set the price at which products are sold. In the case of household appliances, they have a great deal of influence as these markets tend to be very concentrated. In 2011, Whirlpool Corporations, AB Electrolux, General Electric Company, and LG Electronics represented 90% of the sales of major household appliances in the US (Alegria et al., 2012). In the UK, competition on the refrigerator market is seemingly more intense as the top 5 companies represent around 46% of sales in our data for each year of the study period. However, product differentiation reduces competition as soon as we look at specific categories of products. For example, if we consider homogeneous segments of refrigerators or refrigerators-freezers that are either built-in or freestanding and of a specific energy efficiency class, the top 5 represent around 67% of sales in each segment.

In this paper, we consider both the role of potential consumer myopia and imperfect competition on energy consumption of refrigerators sold in the UK market. We use annual product-level panel data from 2002 to 2007 to analyze

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[1] 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. However, principal-agent problems can also arise when one party makes a decision related to energy use, and 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.

two types of decisions: consumer purchase decisions and suppliers' price-setting decisions. Next, we use our estimates to identify counterfactual scenarios with perfect competition and without consumer myopia. This gives us an estimate of the size of the energy efficiency gap which is defined in this paper as the difference between actual average energy consumption of sold appliances and the hypothetical consumption that would be observed in a perfectly competitive market with non-myopic consumers.

Our approach provides a more comprehensive measurement of the energy efficiency gap than that available in the literature. As mentioned above, existing works mostly concentrate on demand inefficiencies as illustrated by the recent reviews by Allcott and Greenstone (2012) and Gillingham and Palmer (2014). We go further, by examining the role of suppliers and imperfect competition.[2] We however limit ourselves to a study of the short-run equilibrium, where suppliers only choose prices, once product characteristics have been chosen. The impact of product innovation is left for future research. We also do not deal with all the imperfections that may influence energy use. In particular, we rule out any considerations related to the pricing of environmental externalities related to energy production and use or principal-agents problems [3] Our contribution to the relevant empirical literature is discussed in more detail in the next section.

[2] 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), and Goldberg (1998). In contrast with our paper, these studies do not seek to measure the size of the energy efficiency gap. Rather they evaluate specific policy scenarios (e.g. standards, feebates, energy labeling, etc.). A limited industrial organization literature has also examined the functioning of appliance markets (e.g. Ashenfelter et al., 2103; Spurlock, 2014).

[3] We also do not investigate how certain policies or regulations might alter the functioning of the markets. As an illustration, trade barriers may have hindered the imports of non-EU refrigerators during the study period. As appliances produced by well-known European brands tend to be more energy efficient than non-EU brands, removing barriers would increase energy use.

Although there is no universal definition of the energy efficiency gap, we are aware that our definition is not the most common, as we depart from the view that limits the energy efficiency gap to consumer behavior. We are however not the only scholars who integrate supply-side inefficiencies as a cause of the wedge between actual and optimal energy use (for instance, see the papers by Jaffe and Stavins (1994) or Gerarden et al. (2015)). One could question the relevance of integrating both demand-side and supply-side inefficiencies in a unified framework instead of studying these imperfections separately. Such a global assessment is necessary if the purpose of measuring the energy efficiency gap is to identify and justify desirable policy intervention, a point made before us by Fischer (2005) and, more recently, by Gerarden et al. (2015) who stress the importance of supply-side factors when designing policies to promote energy-efficient household appliances. Take the example of the subsidies on energy-efficient goods that are recommended by some economists to mitigate demand inefficiencies (e.g. Allcott, Mullainathan, and Taubinsky, 2014) and widely implemented in practice. If producers benefit from lower markups on energy-efficient goods than on less efficient ones – as is the case in the UK refrigerator market in this paper – then subsidies should be lower than they would be if prices were equal to marginal costs.[4]

We model demand using a standard discrete choice model with differentiated quality based on Berry (1994). 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 the simultaneous determination of refrigerator prices and quantities, our instrumentation strategy incorporates data from two outside product markets – freezers and washing machines – which present

[4] Another option would be to adjust antitrust regulations, which is the primary policy tool to mitigate imperfect competition concerns. However this tool was not initially conceived for sector-specific adjustments.

different demand characteristics but technical similarities that lead production costs to be correlated. Choices made by suppliers in terms of prices and products offered on the market are estimated using reduced-form equations that impose few restrictions on how they compete on the market. More specifically, the price equation is estimated with a fixed-effect model in which shocks on market shares are used to identify the size of mark-ups. We identify the model using instruments that exploit a well-known effect in the marketing field, i.e. "extremeness aversion" (Simonson and Tversky, 1992), which affects demand for specific goods in a way that is unrelated to product features in absolute terms, and thus is not systematically correlated with production costs.

What transpires from our estimates is that the impact of the two market imperfections on energy consumption is limited. On the demand side, we find that consumers underestimate future energy savings by 35% in our base specification which assumes a financial discount rate of 4.6%. This suggests investment inefficiencies of reasonable size, which is equivalent to applying an implicit discount rate of 11% to the stream of future electricity costs when calculating the net present value. In line with these numbers, our simulations show that myopia increases energy use by only 9.2% compared to a scenario in which consumers would correctly value future energy costs.

The impact of imperfect competition is also modest, but goes in the opposite direction: it reduces energy use by 4.2% compared to a scenario with perfect competition. The reason is that products that consume more energy have higher market shares on average. Suppliers thus have more latitude to raise their price, which reduces demand. This pattern is likely to be true in other markets of energy-using consumer durables where competition is less intense or demand elasticity is lower for energy-intensive models. As the two imperfections exert opposite effects, the joint effect is a modest 7.2% increase in energy use compared to a perfectly competitive market with fully rational consumers.

These simulations therefore suggest that there would be few energy savings to expect from reaching a fully competitive market with non-myopic consumers.

Likewise, we show that consumer myopia and imperfect competition have limited impact on social welfare (excluding environmental externalities, but including consumer surplus and profits). Consumer surplus[5] would increase by around £76 per sale in the first best optimum – just under 26% of the price of appliances – but most of this increase is a transfer from suppliers, as the overall increase in social welfare is only £18.10. These numbers convey an important message about public policies targeting the energy efficiency gap. With the exception of energy labeling, which seems to have been sufficient to mitigate imperfections in the UK refrigerator market, policies should primarily be concerned with the traditional environmental externality problem.

The rest of the paper is structured as follows. In the second 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 the conceptual framework. Section 4 presents the data. Section 5 outlines our empirical strategy and addresses identification issues. Estimation results are presented in Section 6. In Section 7, we run simulations to predict the impacts on the energy consumption of sold appliances and evaluate the welfare impacts of imperfect competition and consumer myopia. Section 8 summarizes our findings and formulates policy implications.

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[5] Note that consumer surplus includes the utility that consumers derive from the other non-energy related attributes of the products they purchase.

2. Related literature

The empirical literature on the energy efficiency gap in the residential sector is well developed. As explained above, the majority of existing papers focus on demand and consumer myopia. Following the work of Hausman (1979) on room air conditioners, early research found implicit discount rates that are substantially larger than real financial discount rates. In the case of refrigerators, the reported rates range from 39% to 300% (Revelt and Train, 1998; Hwang et al., 1994; McRae, 1985; Meier and Whittier, 1983; Gately, 1980). More recent studies have suggested lower rates. For refrigerators, Tsvetanov and Segerson (2014) find discount rates in the 13-22% range in a study that looks at the impact of energy labeling on consumer surplus. 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 that explain why recent works, including ours, find lower discount rates than earlier studies. The most important reason is the use of panel data, which allows better control of unobserved product characteristics. Indeed, using a hedonic pricing model on a cross section of products as done by Hausman (1979), we find a discount rate of 210% (shown in online Appendix K). Another reason may also relate to the fact that consumers are better informed. For example, energy labeling has been mandatory in the European Union for many appliances, including refrigerators, since 1995. In the US and in Canada, the “Energy Star” label is increasingly used.

As mentioned in the introduction, the main contribution of this paper is to examine the potential influence of suppliers on the energy efficiency gap. A few empirical papers also look at the supply side of energy-consuming durables markets. However, their question is different as they evaluate the impact of a particular policy: fuel efficiency standards (Goldberg, 1998; Jacobsen, 2013), feebates (e.g., d'Hautfeuille et al., 2013), energy labeling (Houde, 2014a, 2014b), and fuel taxes (Verboven, 2002).

Refrigerators constitute a suitable case to explore these questions for reasons that are best explained through a comparison with motor vehicles, for which the impact of gasoline prices has 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. As a result, future energy consumption is exogenously determined by the characteristics of the product. This suppresses an important source of bias and 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 make several assumptions to deal with this issue. See for instance Jacobsen (2013), Li et al. (2009) or Allcott and Wozny (2014). 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 done in this paper and many others.

3. Conceptual framework

In this section, we propose a framework including two components. First, a demand model describes consumer purchase behavior; it serves to measure the size of consumer myopia. Second, a price model describes the pricing behavior of the suppliers; it aims to understand the impact of imperfect competition on the market.[6]

3.1 Demand

We develop a simple discrete choice demand model of the refrigerator market based on Berry (1994). T markets each represent 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 refrigerator models.

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]

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

In this expression, u_{jt} captures the usage value of the refrigerator j over its lifetime which depends on product characteristics such as size and 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

[6] The framework described hereafter is static. A dynamic framework would be useful if our aim were to explain the timing of consumers' purchase decisions, for instance like Rapson (2014), who uses a dynamic model to understand the adoption of energy-efficient air conditioning in the US, since purchase decisions can be delayed for several years. In contrast, the date of purchase of a new refrigerator is mostly exogenous as they are typically replaced immediately when they break down or when the kitchen is renovated (and renovation is not a consequence of the decision to purchase a new refrigerator). This is why we have chosen a static framework which reduces the need for instrumentation and imposes weaker assumptions.

[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 represent a small fraction of individual income.

captures consumers' perceptions of energy costs. If consumers are perfectly rational, we obtain $\gamma = 1$. 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 get:

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

Berry (1994) generalizes 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 a refrigerator. Normalizing the utility of the outside option V_{i0t} to zero, the market share of product j at 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 irrelevance of independent alternatives (IIA) assumption that leads to biased estimates in heterogeneous, segmented product markets.

[8] Here, the modeling strategy is to adopt the standard rational choice model, except that we include the parameter . 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.

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:

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

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 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. The final model therefore includes 8 nests (2 x 2 x 2). This choice is based on our belief that these three characteristics naturally divide the products into 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 size is strongly influenced by family characteristics (size, food consumption habits, etc.) and dwelling characteristics, whereas built-in refrigerators are more likely to be chosen by consumers who are refurbishing their kitchen at the same time. In Appendix

[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 (such as exterior finish, electronic readouts, reliability, and automatic ice makers) 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.

A, we run models with alternative nest structures and the results are 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 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:

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

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.

3.2 Supply

In contrast to the demand equation, we adopt a reduced-form approach to assess the impact of imperfect competition on prices. Previous empirical contributions that examine supply-side issues (see the literature review above) generally adopt a structural approach in which multi-product manufacturers compete à la Bertrand. In the context of a nested logit model, Berry (1994) provides the formula applicable to compute equilibrium prices under Bertrand-Nash competition:

$$p_{jt} = c_{jt} + \frac{\frac{1-\sigma}{\alpha}}{1 - \sigma s_{j(g)t} - (1-\sigma) s_{jt}} \tag{3}$$

In this equation, c_{jt} is the unit production cost of model j at time t; σ and α are the parameters also included in the sales equation. As they can be estimated with the demand equation, we could use (3) to directly compute the markups without any additional estimation

However, this equation is likely to convey an incorrect estimation of the markups. In practice, the markup values are heavily influenced by the choice of nest structure (the smaller the nest, the higher the markup). As we lack information to truly detect the real competitors of product j, the choice of nest structure is arbitrary and therefore could very plausibly under- or over-estimate competition intensity.[10] More fundamentally, the Bertrand-Nash setting overlooks the fact that this sector is characterized by the presence of complex vertical relations between manufacturers and retailers, which also sell refrigerators produced by other manufacturers under their own brand name.

A reduced-form approach copes neither with the issue of vertical relations nor with the fact that nests may be wrongly specified, but is at least less reliant on the strong assumption that the real competitors of product j are truly identified. It thus provides a more flexible strategy to identify price margins.

Therefore, to avoid relying on specific assumptions about the structure of competition, we consider that the purchase price is given by:

[10] If we assume no nest at all (σ=0), we find an average markup of £ 119.8 with very little variation across products (£ 119.7 – 120.4). With 8 nests as defined in the base model, the sales-weighted average markup of all products used in the simulation falls to £ 21.6. The lowest markup would be estimated at £ 21.4 and the highest at £ 28, with most products having a markup close to the minimum.

$$p_{jt} = c_{jt} \times \exp F\left(s_{jt}, s_{j(g)t}\right)$$

In this equation, $F(.)$ is a multiplicative term which captures the size of the mark-up as a function of the product market shares s_{jt} and $s_{j(g)t}$. The reader may note that the choice of such a functional form relates to Berry's formula (3) since it includes the same determinants for the size of the markups. However, it is less restrictive, as it does not include the parameters σ and α that are also present in the demand equation. The main difference with the structural approach is then that additional assumptions will be made at the simulation stage, that is, when using the econometric estimates to compute e.g., the size of the energy efficiency gap. This makes it easier to check whether they are valid, a point made by Busse, Knittel and Zettelmeyer (2013) for instance. In this paper, these assumptions are presented in Section 7 where we describe our simulations.

Taking logs and adopting a log linear specification for F, the price equation becomes:

$$\ln p_{jt} = \ln c_{jt} + m_j + \eta \ln s_{jt} + \varsigma \ln s_{g(j)t} \qquad (4)$$

where m_j is a product-fixed effect influencing the level of the mark-up and $s_{g(j)t}$ is the global market share of product j 's nest in year t. The log-log functional form implies that a relative increase in market share is assumed to have a constant relative impact on prices.

As mentioned above, this approach overlooks the long-run impact of imperfect competition and consumer myopia on product characteristics and innovation. In a preliminary stage of this research, we however applied a dynamic probit model to our data in order to estimate product entry and exit. Results are mostly similar to the ones obtained in the short run. The methodology and results obtained are available on demand. However, this supplementary analysis does not look at manufacturers' capacity to reduce the cost of producing energy-efficient products in the long run. In the absence of cost information, this question cannot be treated easily.

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). The data includes detailed annual information on refrigerators and combined refrigerator-freezers sold in the UK. 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). Note that products that are similar in all respects but have a different brand name are considered to be different. This is in line with the view that brand name is a product attribute valued by consumers for itself. [11]

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

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

estimates lifetimes of 12.8 years for refrigerators and 17.5 years for combined refrigerator-freezers (AMDEA, 2008).[12]

A potential problem is that the data does not include information on energy efficiency policies that may have influenced market outcomes. However, there was no change in the design of the labeling scheme or in the strictness of the regulatory standards during the sample period. Admittedly, the Energy Efficiency Commitment (EEC) scheme was enforced during the study period, offering eligible households the possibility of financial support for the purchase of energy-efficient cold appliances. However, the measure had very little impact on the refrigerator market. In practice, support mostly focused on energy-efficient light bulbs and home insulation. Lees (2008) reports that fridge-freezers subsidized by EEC represented 0.43% of the market between 2005 and 2008. If we also include subsidies from local authorities and the Warm Front, subsidized appliances probably represented around 1.5% of all cold appliances sold between 2005 and 2008.

We drop observations with low sales. In particular, we drop models where annual sales never exceed 100 units over the study period. This ensures that the models in the sample were actually commercialized on a large scale (not only in a few local markets) during at least one year over the period. We also drop observations (product-year) with less than 10 units sold to avoid having models with sales near zero, which would make the estimation of the discrete choice model unstable. Outliers are also dropped: we identify the 2.5% of products with the highest and lowest prices, capacities and energy

[12] The assumption that all appliances of a given type have the same lifetime disregards the fact that some appliances may in fact have a longer/shorter expected lifetime. However, if consumer expectations about lifetimes are constant over time, these cross-sectional differences between appliances will be resolved when using either fixed effects or first differences to estimate our econometric models. We furthermore show in the Appendix that changing the lifetime of appliances when calculating operating costs has limited impacts on the estimated parameters. This is because, on average, appliances have a long lifetime compared to the implicit discount rate applied by consumers.

consumptions, in addition to the 2.5% of products with the highest sales levels. Any product falling 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 of the demand equation. The total number of differences used in the econometric estimation is then 1,365. Descriptive statistics are based on the 2,265 observations used to construct the differences of the estimation sample of the market share equation. Most appliances are larder fridges and fridge-freezers.

Although the data is not used in our estimation, we also know the product's classification according to the EU energy label. Energy labeling has been 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 across different classes. Table 2 provides an overview of the distribution of prices and market shares across energy efficiency classes. Note that almost all products were rated A, B or C during the study period.

Table 1: Summary statistics on product characteristics

Variable	Unit	Mean	Std deviation

[13] Outliers in terms of price, capacity, energy consumption and sales are excluded for several reasons. First, the data is reported to GfK and some observations appear to have been miscoded. We want to remove from the data observations with absurd values. Second, we exclude niche products, since they would not properly belong to the nests we have defined. We also exclude best sellers because we do not observe commercialization strategies that can be correlated with prices or energy efficiency and fear that these products have access to a much wider web of providers than other goods. Tests have been run to check that our results were not heavily dependent on how the sample was restricted.

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	liters	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" labeled 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".

The data also suggest the degree of imperfect competition prevalent in the market. Restricting to 2007 for simplicity, the refrigerator market was composed of 66 manufacturer brands, selling an average of 25 different products each. A few brands concentrated most of the sales: the top 5 and top 10 manufacturers respectively commercialized 48% and 68% of all the products sold in that year. However, market shares of these top manufacturers have a similar size, none of them exceeding 20%. As a result, the Hirschman-Herfindhal Index (HHI) was around 770 at the global 2007 level, which does not suggest strong market power.

These numbers however ignore the existence of product differentiation. Refrigerators have radically different sizes and energy efficiency levels. They can also include specific features, such as water and ice dispensers or free-frost technology to make maintenance easier. Some consumers buy built-in appliances to fit better in their kitchen whereas others opt for freestanding appliances, etc. As a result, a given product actually has a fairly limited number of direct competitors. We thus need to reassess the degree of imperfect competition by calculating HHI for specific market segments. For example, consider eight market segments of refrigerators or refrigerator-freezers, that are either built-in or freestanding and either above or below the median size. The HHI lies above 1,500 (moderate concentration) in 3 cases out of 8. If we further breakdown the market based on the energy efficiency rating of appliances, this produces a total of 37 sub-segments of refrigerators or refrigerator-freezers that are either built-in or freestanding, of a comparable size and with the same energy efficiency rating. The HHI is above 2,500 (high concentration) in 23 of these sub-segments.

We now explain how we derive the electricity cost variable from the 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 (Γ_j) and lifetime (L_j) of each model available on the market. He considers the opportunity cost of capital when determining the appropriate discount rate.

Choosing the value of r is critical as it directly influences γ, and thus the importance of consumer myopia. Consider first a consumer who purchases a refrigerator from her/his savings. The opportunity cost is then related to the return that could be made on these savings. More precisely, the discount rate r should equal the real average bond deposit rate of UK households (2.83% according to the Bank of England for the period 2002-2007).[14] Consider then a consumer who buys on credit. Now her/his opportunity cost corresponds to the average interest rate. A possible reference is the rate of credit card lending (13.98% according to the Bank of England for the period 2002-2007).[15] Accordingly, the discount rate to be applied should be a weighted average of both these rates where weights equal the share of both types of consumers. In this study, we use statistics on method of payment for furniture available in the UK food and expenditure survey. In 2007, 2.06% of respondents who purchased furniture used a loan, 1.98% hired their product, 11.90% used a credit card and the remaining 84.06% used cash or another method of payment.[16] Assuming the same patterns for refrigerators - products present similarities, in particular, similar average prices, we have considered that the proportion of consumers likely to use a credit card loan or a similar type of loan for the purchase of a refrigerator is around 16%. Using this weight, we find a discount rate r equal to 4.6%.[17]

Measuring the forecasted electricity price q^f_{t+s} is more problematic as we only observe real electricity prices. Furthermore, there was a drastic surge in electricity prices in the UK over the period, implying that observed and expected electricity prices could very well differ. As a benchmark, we

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[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.

[15] The nominal rate was 15.76% and the Bank of England code for the statistics is IUMCCTL. We subtracted the average inflation rate of 1.78% between 2002 and 2007.

[16] The survey does not describe these other methods, which would include, to our understanding, debit cards and cheques.

[17]

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 of 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:

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

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 of the data that are observed at each time period. This implies that the model is updated 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:

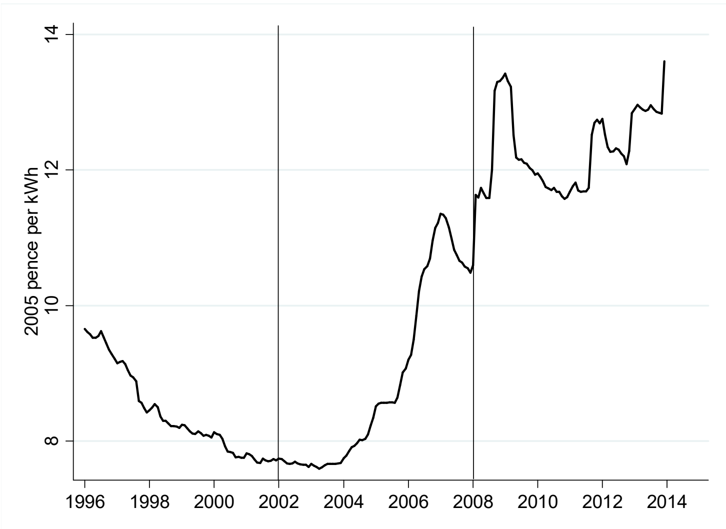
$$q_{t+s}^{f} = \hat{a}_t + \hat{b}_t q_{t+s-1}^{f} \tag{5}$$

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 C.

In online Appendix M, we also 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 obtain 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 rather to describe cost valuation by a sophisticated decision-maker so that the parameter γ only captures the size of the deviation from this benchmark.[18]

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).

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



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

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 pre-2002. Consequently, forecasts are consistently below actual prices during the period, i.e. an error that decreases the size of γ.

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

5. Estimation

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

5.1 Demand

To derive an econometric specification for short-term sales, we first add year dummies λ_t to eq. (1) to eliminate the share of the outside option and any shift in the overall market share level. Next we take the first-difference in order to eliminate the value of usage.[19] This leads to:

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

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 $s_{j(g)t}$. An instrumental variable approach is therefore 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

[19] We use first-differencing instead of demeaning since this allows us to directly estimate and in a non-linear GMM estimation. A first-differencing is only efficient when there is no serial correlation. When testing for serial correlation in the first-differenced model using a Wooldridge test, we find evidence of serial correlation. We account for serial correlation in the estimation of the standard errors using clustered robust standard errors at the product level. A fixed effect specification in level is displayed in online Appendix I. The estimated coefficients in the first-differenced and fixed effects models are comparable in size and not statistically different from each other.

average transaction price calculated by GfK.[20] Applying a valid instrument on prices addresses *de facto* the attenuation bias caused by measurement errors.

A common instrumentation approach in industrial organization is to take advantage of the fact that the market is imperfectly competitive. In such situations it is claimed that non-price 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 to. This approach is extended in Berry et al. (1995) and has been adopted in many studies.

A weakness of this strategy is that taste shocks that affect other products can also influence the utility of product j. For instance, marketing efforts by a firm can induce a taste shock that affects all of its products, or given characteristics that concern several models might become popular among consumers. The fact that refrigerators are quite standardized products, except in the dimensions we base the nests on, is not necessarily advantageous when instrumenting with other products' characteristics. This means that unobserved product characteristics are likely to be correlated across nests and manufacturers. Significant standardization also implies that product characteristics may not evolve sharply over time and therefore that within and outside nest averages they may remain stable from one year to the next, reducing the strength of potential instruments. We indeed find that when we use instruments of this type, they are weak (shown in online Appendix L).

This leads us to adopt an alternative approach where instruments are related to the price of products sold in two related markets: the upright freezer market (i.e. excluding the chest freezer market) and the washing machine market.

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

Freezers and washing machines present two useful characteristics. First, they are sold outside the refrigerator market, and thus to different consumers. This implies that taste shocks are less likely to be correlated with those observed in the refrigerator market. Second, they share some technical similarities with refrigerators as they are all large household appliances. This means that shocks affecting production costs – e.g., an increase in steel prices – are likely to be correlated across these markets. The prices of freezers and washing machines are therefore likely to be correlated with cost shocks in the refrigerator market. This approach presents some similarities with the strategy implemented by Hausman et al. (1994), which uses prices of the same product in other regions (and thus in different markets) as instruments. We use the price of similar products in other markets. The common identification assumption is that prices in outside markets reflect underlying product costs and stochastic market-specific factors that are independent from those observed in the fridge markets.

The difficulty with this approach is to match outside prices to the price of a specific refrigerator, as goods are different. Our solution is to use two product characteristics that are common to refrigerators, freezers, and washing machines, i.e. capacity and whether the appliance is built-in or freestanding. Using a hedonic pricing model, we estimate a year-specific implicit price for these two characteristics on product-level data for the UK freezer and washing machine markets between 2002 and 2007 obtained from GfK. This gives a year-specific average for subcategories of freezers and washing machines, which we match with the same subcategories of refrigerators-freezers and refrigerators. For example, the implicit price of smaller than average built-in freezers at time t is used as an instrument for the price of smaller than average, built-in refrigerators and refrigerator-freezers at time t. Importantly, we include brand-specific time trends in the hedonic pricing model in order to control for changes in brand-specific marketing strategies and image. This ensures that variations in the hedonic prices of the two characteristics do not capture changes in brand image, which could be correlated with the sales of refrigerators with the same brand name. 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 B.

As previously evoked, another issue 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 across regions. However, regional price heterogeneity is likely to be modest. 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 resides. Measurement errors may also arise for two other reasons. First, we have averaged the interest rate on credit card loans and the deposit rate for fixed bound deposits to compute the discount rate. Second, consumer heterogeneity (e.g. in terms of environmental awareness) may lead some consumers to prefer energy-efficient appliances. The sorting of consumers across products (as in Bento, Li and Roth, 2012) would imply that product-specific energy costs are measured with errors and thus endogenous. In Appendix E, we give results with a specification whereby the operating cost is instrumented with its lagged values to control for all potential measurement problems. We find small differences.

A final issue is that we only have access to the average UK electricity prices, whereas perfectly rational consumers are unlikely to 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 did not change between 2002 and 2007, which is plausible as the rise was driven by gas price increases that raised the (variable) cost of electricity generation. However, in Appendix

D we run a robustness test where we assume that the *share* (not the level) of the fixed part remains stable. This slightly inflates the size of γ.

5.2 Supply

For convenience, we rewrite Eq. (4) here

$$\ln p_{jt} = \ln c_{jt} + m_j + \eta \ln s_{jt} + \varsigma \ln s_{g(j)t}$$

To deal with the problem that the production cost is not observed, we assume that $\ln c_{jt} = \lambda_j + \lambda_{b(j)t} + \lambda_{g(j)t} + \epsilon_{jt}$ where λ_j is a product fixed effect, $\lambda_{b(j)t}$, a by-brand by-year fixed effects, and $\lambda_{g(j)t}$, a by-year by-nest fixed effect. ϵ_{jt} captures time-varying shocks on the production cost. Introducing these different fixed effects will absorb the terms $\varsigma \ln s_{gt}$ and m_j. As a result, and slightly abusing notations, the price equation is now:

$$\ln(p_{jt}) = \lambda_j + \lambda_{b(j)t} + \lambda_{g(j)t} + \eta \ln(s_{jt}) + \epsilon_{jt} \qquad (7)$$

The multiple fixed effects allow controlling for most unobserved factors that influence cost. However, there is a price to be paid: It is not possible to estimate the value of m_i and ς econometrically, and thus to directly infer the size of the markup from these estimates. When performing the simulations, we therefore bypass the obstacle using external information on average markups in the UK cold appliance industry.

Obviously, $\ln(s_{jt})$ is endogenous in Eq. (7) for the same reason that p_{jt} was endogenous in the sales equation. But we now need an instrument that is correlated with demand shocks but uncorrelated with costs. Our strategy relies on a well-known effect in the marketing field, i.e. the “compromise effect” (Drolet, Simonson and Tversky, 2002) or “extremeness aversion” (Simonson and Tversky, 1992). This says that demand for differentiated goods is affected in a way that is unrelated to product quality in absolute terms. For example, when faced with three differentiated products with ordered product characteristics, consumers tend to purchase the product with average characteristics. The surprising element is that the characteristics of the average product matter less than its position in the “middle” of all products. This effect has been validated in a wide variety of experimental settings (e.g. Müller et al., 2012).

The distance to the average product can then serve as an instrument because it affects demand, but is not systematically correlated with production costs. To explain why, let us first define the instrument. We use the height of the refrigerator and calculate the average distance for all products in a given nest and year. This average changes over time because new products are launched and others are withdrawn. The instrument is then equal to the squared value of the difference between this average and product *j*’s height. We expect this instrument to be relevant because consumers, if averse to extremes, will favor products whose height is close to the within-nest average. Using height as a product feature to construct our instrument is justified by two reasons. First, it is a very visible product feature that allows for direct and immediate aesthetic comparison in retail shops. Second, height is not binding, as all refrigerators are below standard ceiling height (2.4 meters). This leads to significant variation across models, in contrast with width and depth, which vary less in order to correspond to all kitchen sizes.[21]

The exogeneity condition imposes that our instrument should not be correlated with unexplained supply shocks (i.e. cost shifters) present in the error term. Justifying exogeneity requires detailed explanations. To start with, note that variation is generated by changes in other products' height. One could argue that non-price characteristics of other products are exogenous because they are selected before the pricing decision. This first argument is, however, partly

[21] Height is a non-binding attribute because our sample includes a majority of larder fridges and fridge-freezers which are rarely put under a cabinet. As a result, there is significant within-nest variation in height across models. This variation plays an important role in guaranteeing the strength of our instrument (as described hereafter in the results section with standard statistical tests).

convincing for reasons similar to those put forward when justifying the IV strategy for the demand equation in subsection 5.1. Like taste shocks, time-varying changes in production costs can be correlated across products, and height obviously influences the production cost – a higher refrigerator is likely to be more costly to manufacture. This problem is, however, mitigated by the absence of a systematic relationship between this increase and the *squared* difference in absolute terms between the height and the within-nest average. Imagine for instance a downward shock on product j's distance from the average height, which thus increases demand. If the product is higher than average, this means that the average height has increased (because of the launch of higher-than-average products and/or the withdrawal of lower ones). This shock can be correlated with a change in the production cost, which makes the production of high refrigerators less expensive (e.g. a decrease in steel prices). However, the same change in the production cost will have the opposite impact on our instrument if product j is smaller than average. That is, the distance to the average will increase. The point is that there is no systematic correlation with the costs.

In addition, the inclusion of stringent controls reduces the risk of not meeting the exogeneity restriction. Since our instrument evolves with the average height of products within a nest, it could possibly be correlated with their marginal cost. However, by-nest by-year fixed effects have been included in the regression to extract such correlation from the error term. Likewise, distance to average height could also reflect a specific positioning of firms, and therefore be correlated with firm-specific characteristics. We make sure that this correlation between the instrument and the marginal cost is extracted from the error term by introducing by-brand by-year fixed effects.

Last, to secure our strategy, we account for the possibility that the error term includes time-varying effects of height on production costs: $\epsilon_{jt} = \bar{\epsilon}_{jt} + f_t(H_j)$ where H_j is the height of product j. We then proxy $f_t(H_j)$ using quadratic interaction terms between height and time. This set of additional controls is a sufficient statistic for ensuring that the instrument is not correlated with $\bar{\epsilon}_{jt}$.[22]

The final equation estimated is:

$$\ln(p_{jt}) = \lambda_j + \lambda_{b(j)t} + \lambda_{g(j)t} + \eta\ln\left(s_{jt}\right) + H_j t\left(\epsilon_1 + \epsilon_2 t + \epsilon_3 H_j + \epsilon_4 H_j t\right) + \bar{\epsilon}_{jt} \quad (8)$$

The coefficient of interest is η, which we will interpret as the impact of market power on product prices. This interpretation relies upon the assumption that marginal costs do not depend on s_{jt}, a common assumption in studies on empirical industrial organization (e.g. Berry, 1994). This may be challenged even though Eq. (8) is a flexible specification for marginal costs, which includes by-firm, by-year fixed effects. One could argue for instance that production costs could in fact be correlated with s_{jt} due to learning-by-doing: sustained sales will allow manufacturers to gradually improve their processes, thus reducing production costs. However, learning-by-doing is driven by cumulative sales, not by annual sales. For this to happen, a correlation will need to exist between s_{jt} and cumulative sales. This correlation is arguably weak for two reasons. First, the plants that manufacture refrigerators sold in the UK typically produce for other markets. Second, low sales levels can either correspond to a product launch or a product's end of life. The relationship between annual sales at time *t* and cumulative production is thus typically non-monotonic.

[22] The stringency of the set of controls can be increased by introducing fully interacted fixed effects: by-nest by-brand by-year fixed effects. Hence we would control for firm positioning within each nest and at each time period. This is done in Appendix H. Results lose some precision but are unchanged. Another possibility, also reported in Appendix H, is to introduce nest-specific or brand-specific quadratic trends for the correlation between height and time, which could be different for each nest or brand. Likewise, results are quite similar in magnitude.

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.[23] 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 zero.

The main result in Table 3 is that $\gamma \approx 0.65$, which implies that consumers underestimate energy costs by 35%. Importantly, the 95% confidence interval for γ is 0.36 – 0.95. Hence the estimate of the attention parameter is both statistically different from 0 and 1. Consumers still take a large share (65%) of future discounted operating costs into consideration when purchasing a refrigerator. This is more explicit if we compute the "implicit" discount rate that would rationalize consumer behavior. That is, the value of r necessary to obtain a value of γ equal to one. We show in online Appendix J 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 a moderate distance from the average discount rate of 4.6% used as a benchmark. However, due to the long lifetime of cold appliances, this leads to a relatively large underestimation of energy costs.[24]

[23] The standard empirical approach is to separately estimate the coefficients for the price and the energy costs in a linear setting, and deduce the values of α and γ. We include the results obtained with the standard linear approach as a robustness test in online Appendix I along with standard tests of the validity of instruments.
[24] The longer the lifetime, the smaller the value of for a given implicit discount rate. For the reader interested in comparing estimates of consumer myopia across various studies, the parameter of reference is therefore the implicit discount rate and not the value of since it is influenced by the lifetime of the product under study.

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

Dependent variable	Logarithm of market share of product *j*
Importance of total electricity costs (γ)	0.6538*** (4.32)
Utility for money (α)	0.0052*** (3.51)
Within-group correlation of error term (σ) for the demand equation	0.8889*** (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 refrigerator-freezers, built-in from freestanding appliances, and appliances by capacity (over and below the sample median). *t*-statistics are 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 low when compared with the earlier literature on refrigerators, which found implicit discount rates above 30% (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 decreased because consumers are better informed: energy labeling has been 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 online Appendix K). As argued in Section 2, recent studies that rely on panel data tend to find rates of similar magnitude.[25] The direction of the bias suggests that unobserved quality is negatively correlated with energy use. This is arguably the case in the refrigerator market in which, for a given size class – the hedonic equation includes controls for size, height, and width, energy efficient refrigerators are also more reliable, use better material, exhibit a more sophisticated design and electronic readout.

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 are presented in Appendices (A, D and E) and show little differences in the magnitude of the implicit discount rate. For example, assuming a standard logit model with no nest leads to a value of γ around 0.72.[26]

Prices

Estimation results are shown in Table 4. We use two-stage least squares and cluster-robust standard errors to estimate the price equation. As expected, suppliers adapt prices to shifts in demand: when the market share of an appliance increases by 10%, its price increases by around 0.6%. This effect is statistically significant and of reasonable magnitude.

The relevance of the instrument is suggested by the high Kleibergen-Paap rk Wald F statistic. The output of the first stage is also reported in Table 4. The

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

[26] The reader may notice that our specification assumes that γ is constant across the study period. It is possible that consumers' attention to energy costs increases with the price of electricity. We ran regressions to test whether γ increased in line with the price of electricity. However, results were not conclusive because the panel is short.

negative correlation with the logarithm of the market share and our instrument confirms the idea that consumers might be averse to extremes.[27]

Table 4: Fixed effects 2SLS Estimation results for the price equation

Dependent variable	Log. price of product *j*
Markup, η	0.0627** (2.56)
Year x brand dummies	Yes
Year x nest dummies	Yes
Product fixed effects	Yes
First stage results Square of distance to mean height within the nest	 -0.0008*** (-5.44)
Weak identification test Kleibergen-Paap rk Wald F statistic Max. IV bias	 29.64 <10%
Observations	2,421

Notes. *t*-statistics are 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.

7. Counterfactual simulations

In this section, we perform simulations to quantify the impact of the two identified market imperfections on energy consumption and consumer surplus. We analyze three counterfactual scenarios and compare against the "business-as-usual" situation observed in the data: I) consumers are non-myopic but the market is imperfectly competitive; II) consumers are myopic but the market is perfectly competitive; and III) consumers are non-myopic and the market is perfectly competitive.

Removing myopia in scenarios I and III amounts to substituting the estimates of the attention parameter $\hat{\gamma}$ (equal to 0.65) by 1. Simulating perfect competition in scenarios II and III is more complex. In a competitive market,

[27] We also run an over-identified model using, as an additional instrument, the squared value of our instrument. We also run an over-identification test. The Sargan over-identification test confirms the validity of the instruments.

product prices equal marginal costs $(p_{jt} = c_{jt})$. Given Eq. (3), this would amount to substituting $\ln p_{jt}$ by:

$$\ln p_{jt} - (\widehat{m}_j + \hat{\eta} \ln s_{jt} + \hat{\varsigma} \ln s_{g(j)t})$$

where $\widehat{m}_{jt}$, $\hat{\eta}$, and $\hat{\varsigma}$ are estimated parameters. The problem is that we do not know $\widehat{m}_{jt}$ and $\hat{\varsigma}$ which have been absorbed by the various fixed effects. Our solution involves calibrating markups for individual products based on $\hat{\eta}$ and external information on the average markup prevailing in the corresponding UK manufacturing and retail markets. That is, we substitute $\ln p_{jt}$ by $\ln p_{jt} - (\overline{m} + \hat{\eta} \ln s_{jt})$ where $\overline{m}$ is such that the sales-weighted mean of $(\overline{m} + \hat{\eta} \ln s_{jt})$ is equal to the average mark-up on the market. This leads us to treat all products as if the size of the nest did not matter. This approximation is not too much of a concern. For large nests, competition is high and therefore the within-nest market share should have a low influence on the markup. These larger nests represent most of the market (in 2007, the 4 largest nests represented 82% of the market). Our approximation may wrongly estimate the markups in smaller nests, even though, within each nest, the ranking of the markups is properly estimated, implying that we can correctly identify, within each nest, which products have the highest markups. We have checked that this issue did not create strong distortion by estimating the impacts of the simulation while considering only the 4 largest nests. The results obtained in this case were very similar to those obtained when considering all nests.

The average markup is estimated with the method introduced by Roeger (1995) and adapted to firm-level data by Görg and Warzynski (2006). This approach allows us to estimate average markups prevailing in a sector based on standard financial data. In practice, we extract financial data from ORBIS on a large sample of UK firms that manufacture electric appliances or sell these goods and obtain an estimated average of 19.6% for the manufacturing and retail of electric appliances in the UK.[28] This markup includes both the markup of manufacturers (8.6%) and retailers (11%). Its value is in line with other studies (for instance, see Görg and Warzynski, 2006). Methodological details on Roeger's approach and estimation tables are provided in Appendix (F). In addition, we perform robustness checks (G) by considering values of mark-ups equal to the limits of the 95% confidence interval (9.9%-29.3%). Simulation results are of similar magnitude.

We also assume that the total amount of sold appliances is the same under all scenarios.[29] This is not unrealistic since purchases of refrigerators are mostly replacements; hence the number of sales is unlikely to be affected by the increase in electricity prices because the refrigerator market is saturated. However, increases in electricity prices 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.

Impact on energy use

To compute energy consumption in the three scenarios, we first use the estimates of the sales and price equations to predict product j's market shares s_{jt} and price p_{jt} in the simulated equilibria. Taking the example of scenario I, we set $\gamma = 1$ in the demand equation and first calculate the corresponding demand holding the price fixed. To account for price adjustments, we then update prices after the demand change and then recalculate market shares recurrently until a new equilibrium is reached. Based on the market shares estimated for each product and each scenario, we calculate a market average

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29 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.

for the energy consumption of sold appliances and compare it to the business-as-usual scenario.

Energy consumption levels in each scenario are presented in Table 6, along with appliance capacity and the energy consumption of the appliance per liter of capacity. The key finding is that the two market imperfections have opposite impacts on energy use. As expected, myopia increases energy use. Further, our expectation is that myopia is moderate. Table 6 confirms this: maintaining other factors constant, the sales-weighted average energy consumption of a sold refrigerator increases from 281.6 kWh/year to 310.2 kWh/year. This corresponds to a 9.2% increase. In contrast, imperfect competition reduces energy use by 4.2%. The reason is that larger appliances (which consume more energy) have higher markups on average. Suppliers thus have more latitude to raise their price under imperfect competition, which reduces demand.

As the two failures exert opposite influences on energy use, the market yields a level of energy performance that is only slightly higher than the level that would be observed in a perfectly competitive market with fully rational consumers (+7.2%, 310 kWh/year versus 288.0 kWh/year). All in all, these simulations suggest that the business-as-usual energy consumption level is not far from a perfectly competitive market with fully rational consumers.

Table 6: Simulated impacts of myopia and imperfect competition on the energy consumption of sold appliances

	Energy consumption (kWh/year)	Appliance capacity (litres)	Energy cons-umption per litre (kWh/year/litre)
Observed situation	310.2	235.2	1.32
Non-myopic consumers	281.6	219.0	1.29
Perfect competition (zero mark-ups)	323.4	247.8	1.31
Perfect competition and non-myopic	288.0	225.7	1.28

consumers	

Interestingly, the main margin of adaptation for consumers to reduce energy consumption seems to be appliance size, and not appliance energy efficiency. When consumer myopia is withdrawn, energy consumption per year and per liter of capacity decreases by around 2.2%, whereas appliance capacity concomitantly decreases by 6.9%. Likewise, a reduction in appliance price caused by imperfect competition increases appliance size (by 5.4%), but only slightly improves energy efficiency (by 0.8%).

This pattern is likely to be true in other durable goods markets in which competition is usually more intense for smaller products. In particular, the fact that larger durable products, which use more energy, have higher markups is likely to be true in the automobile market as shown by Berry, Levinsohn and Pakes (1995, see Table V p. 879) who have estimated lower elasticities for larger, energy-consuming cars.

We are not aware of any study providing demand elasticity estimates as a function of energy consumption for other energy-using consumer durables. However, we have access to GfK data on the UK market for washing machines and dishwashers that are equivalent to the data on refrigerators used in the study. Running a simple OLS univariate regression (see the results below in Table 7), we find a statistically significant positive correlation between sales and energy consumption for washing machines. We do not find significant results for dishwashers. Incidentally, Galarraga et al. (2011) find that demand for dishwashers bearing energy labels signaling greater energy efficiency is more price elastic than demand for non-labeled products. The estimation however controls for size, which obviously influences energy consumption.

Ultimately, it seems difficult to conclude that demand elasticity is always positively correlated with the level of energy use for all consumer durables. This justifies the need to conduct similar analyses in other markets.

Tableau 7: The correlation between energy consumption and sales for washing machines and dishwashers in the UK

Product type	Annual energy consumption†	Data coverage
Washing machines	+473** (2.16)	2002-2007
Dishwashers	-167 (0.29)	2006

†: the coefficient for an additional unit of annual energy consumption on sales. This is obtained by regressing the energy consumption variable on sales in a linear regression. The regression for washing machines includes time dummies to account for changes in the average energy efficiency of products over time. We do not include these dummies for dishwashers because we have only one time period. T-statistics in brackets.

Impact on consumer surplus, profits and social welfare

Assuming that the externalities from energy consumption are already internalized in the electricity price, social welfare is the sum of consumer surplus and profits. Profits can easily be computed as the product of sales and markups under the assumption that product *j*'s unit production cost does not change across scenarios. The average consumer surplus is obtained using the formula in Small and Rosen (1981) adapted to the nested logit framework by Alcott and Wozny (2011):

$$CS = \frac{1}{\alpha}\ln\left[\sum_{g}\left[\sum_{j(g)} exp\left(\frac{V_{jt}}{1-\sigma}\right)\right]^{1-\sigma}\right] + \Delta$$

where Δ is a constant. Importantly, this formula is based on the utility V_{jt} that is *perceived* by consumers. When consumers are myopic, the surplus actually *experienced* by consumers is below *CS* because of the unforeseen energy costs. On average, these are equal to:

$$\frac{1}{T}\sum_{t}\sum_{j} s_{jt}(1-\gamma)C_{jt}$$

Under myopia, we adopt a paternalistic view to calculate social welfare and adjust the consumer surplus to account for unforeseen energy costs (see Allcott and Wozny, 2011, for a discussion).

The parameters α and σ have been econometrically estimated. The value of Δ is irrelevant as we are interested in the difference in consumer surplus with the BAU scenario. We thus just need to make an assumption on the market share of the outside good. s_0 is assumed to be equal to the share of UK households that do not possess a refrigerator or a refrigerator-freezer, estimated at 1% by BRE (2013).

Simulation results are displayed in Table 7. Withdrawing either imperfect competition or consumer myopia obviously increases consumer surplus. But the impact is relatively modest: an increase of £65 for shifting to perfect competition and £23 for removing myopia (respectively around 22% and 7.5% of the purchase price of sold products). The impact on social welfare is much smaller because most of the gain in the consumer surplus is a transfer from suppliers. In particular, the first best scenario with no imperfections only improves social welfare by £18.10 relative to the business-as-usual scenario. This corresponds to 6.1% of the average refrigerator price.

Table 7: Welfare impacts of myopia and imperfect competition for an average sale (2005 £)

Welfare impacts *	Consumer surplus	Profit	Social welfare
Withdrawing myopia	+22.9	-12.8	+10.1
Shifting to perfect competition	+66.6	-58.1	+8.5
Both	+76.2	-58.1	+18.1

* When myopia prevails, we have subtracted unforeseen energy costs from the consumer surplus. The sales-weighted average price of products included in the welfare evaluation is £296. Since profits are null under perfect competition, the profit loss is the same when shifting to perfect competition or shifting to perfect competition without myopia: it corresponds to the average profit in the "business-as-usual" situation.

8. Conclusion

While the empirical literature on the energy efficiency gap in the residential sector has primarily focused on consumer behavior, this paper develops a comprehensive view of both demand-side and supply-side behaviors that occur in the UK refrigerator market. This allows us to investigate the influence of two market imperfections: the fact that consumers underestimate future energy costs and imperfect competition, which allows suppliers to charge prices above marginal production costs.

We obtain results that moderate the importance of the intensively discussed problem of the energy efficiency gap. We find that consumers undervalue future energy costs by 35%, 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. This leads to a 9.2% increase of average energy use of sold appliances relative to a scenario with perfectly rational consumers. Imperfect competition yields an opposite impact as it reduces energy use by 4.2%. The joint effect of both imperfections is a modest 7.2% increase. The observed energy consumption level is thus not far from a perfectly competitive market with fully rational consumers. The welfare evaluation confirms this result: social welfare per refrigerator sold would only be £18.10 higher in the first best optimum. This corresponds to 6.1% of the average refrigerator price.

These empirical finding thus suggest a limited need for public policies to restore efficiency in the refrigerator market. Notwithstanding, one should obviously be cautious when deriving general policy implications, as the UK refrigerator market may present specificities. For example, energy labeling has been mandatory since 1995, which has arguably reduced myopia. This obligation however applies to all energy-using appliances sold in the European Union and labeling is also observed in many markets outside this region. However, to date no investigation has been made of how policies promoting energy efficiency mitigate or exacerbate the market power problem, and this analysis is left for future research.

Finally, an important limitation is that the analysis does not account for the long-run impact of consumer myopia and imperfect competition on product innovation. This weakness – observed in almost all empirical papers on the energy efficiency gap – probably leads to an underestimation of the size of the inefficiencies. For instance, myopia reduces manufacturers' incentives to launch energy-efficient refrigerators and withdraw inefficient models, an effect that is not analyzed here.

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References

Alegria, A., Kaczanowska, A. and L. Setar, 2012. Highly Concentrated: Companies That Dominate Their Industries. IBISWorld, Special Report February. http://www.themarketworks.org/sites/default/files/uploads/charts/Highly-Concentrated-Industries.pdf. Accessed: 2 July, 2015.

Allcott, H. and M. Greenstone, 2012. "Is There an Energy Efficiency Gap?" *Journal of Economic Perspectives*, Volume 26, Issue 1, Pages 3–28.

Allcott, H. and N. Wozny, 2014. "Gasoline Prices, Fuel Economy, and the Energy Paradox," *Review of Economics and Statistics*, Volume 96, Issue 5, Pages 779 –795.

Allcott, H., Mullainathan, S., & Taubinsky, D., 2014. Energy policy with externalities and internalities. Journal of Public Economics, 112, 72–88. http://doi.org/10.1016/j.jpubeco.2014.01.004Anderson, S.T., Kellogg, R. and J.M. Sallee, 2013. "What do consumers believe about future gasoline prices*?"* *Journal of Environmental Economics and Management*, Volume 66, Issue 3, Pages 383–403.

Ashenfelter, O. C., Hosken, D. S., & Weinberg, M. C., 2013. The Price Effects of a Large Merger of Manufacturers: A Case Study of Maytag-Whirlpool. *American Economic Journal: Economic Policy*, 5(1), 239–261. http://doi.org/10.1257/pol.5.1.239.

Association of Manufacturers of Domestic Appliances (AMDEA), 2008. "The Time to Change Programme: Encouraging Energy Efficiency in UK Households," Presentation at the occasion of EU Sustainable Energy Week, 29th January 2008.

Atkins and ECN, 2006. Impact Assessment on the Future Action Plan for Energy Efficiency (CLWP: 2006/TREN/032). Final Report.

Bank of England, 2013. Statistical Interactive Database, consulted on October 28, 2013.

Bento, A. M., Li, S., and Roth, K., 2012. "Is There an Energy Paradox in Fuel Economy? A Note on the Role of Consumer Heterogeneity and Sorting Bias," *Economics Letters*, *115*(1), 44-48.

Berry, S.T., 1994. "Estimating Discrete-choice Models of Product Differentiation," *The RAND Journal of Economics*, Volume 25, Issue 2, Pages 242–262.

Berry, S.T., Levinsohn, J. and Pakes, A., 1995. "Automobile Prices in Market Equilibrium," *Econometrica*, Volume 63, Issue 4, Pages 841–890.

BRE, 2013. *Energy Follow-up Survey 2011. Report 9: Domestic Appliances, Cooking and Cooling equipment*. Prepared by BRE on behalf of DECC.

Busse, M.R., Knittel, C.R. and F. Zettelmeyer, 2013. "Are Consumers Myopic? Evidence from New and Used Car Purchases," *American Economic Review*, Volume 103, Issue 1, Pages 220–256.

Committee on Climate Change, 2011. Household Energy Bills – Impact of Meeting Carbon Budgets, UK.

Competition Commission, 1997. Domestic Electrical Goods II: a Report on the Supply in the UK of Washing Machines, Tumble Driers, Dishwashers and Cold Food Storage Equipment, UK.

D'Hautfeuille, X., Givord, P. and X. Boutin, 2013. "The Environmental Effect of Green Taxation: the Case of the French "Bonus/Malus," *Economic Journal* (Features), Volume 124 (August), Pages 393–419.

Defra, 2009a. *Global Carbon Impacts of Energy Using Products*. Market Transformation Programme.

Defra, 2009b. *Saving Energy through Better Products and Appliances*.

Defra, 2010. *BNCO02: Domestic Chest Freezers, Upright Freezers, Fridges and Fridge-freezers: Government Standards Evidence Base 2009: Reference Scenario, Version 1.1*.

Department of Energy and Climate Change (DECC), 2013a. Domestic energy price statistics, including "Retail prices index: fuels components monthly figures" and "Average annual domestic standard electricity bills for selected towns and cities in the UK with average unit costs", last update May 2013, UK.

Department of Energy and Climate Change (DECC), 2013b. "Average variable unit costs and fixed costs for electricity for selected towns and cities in the UK," *Annual domestic energy bills*. Domestic energy price statistics.

Drolet, A., I. Simonson and A. Tversky, A., 2002. "Indifference curves that travel with the choice set," *Marketing Letters,* Volume 11, Issue 3, Pages 199–209.

European Commission, 2011a. *Energy Efficiency Plan 2011*, COM(2011) 109 final.

European Commission, 2011b. *Roadmap to a Resource Efficient Europe*, COM(2011) 571 final.

Fischer, C., 2005. "On the Importance of the Supply Side in Demand-Side Management," *Energy Economics*, Volume 27, Issue 1, Pages 165–180.

Galarraga, I., González-Eguino, M., & Markandya, A. (2011). Willingness to pay and price elasticities of demand for energy-efficient appliances: Combining the hedonic approach and demand systems. Energy Economics, 33, S66-S74.

Gately, D., 1980. "Individual Discount Rates and the Purchase and Utilization of Energy-using Durables: Comment," *The Bell Journal of Economics*, Volume 11, Issue 1, Pages 373–374.

Gerarden, T.D., Newell, R.G., Stavins R.N., 2015. "Assessing the Energy-Efficiency Gap". NBER Working Paper No. 20904.

Gillingham, K. and K. Palmer, 2014. "Bridging the Energy Efficiency Gap: Policy Insights from Economic Theory and Empirical Analysis," *Review of Environmental Economics & Policy*, Volume 8, Issue 1, Pages 18–38.

Goldberg, P. K. 1995. "Product Differentiation and Oligopoly in International Markets: The Case of the U.S. Automobile Industry," Econometrica, Volume 63, Pages 891-951.

Goldberg, P. K. 1998. "The Effects of the Corporate Average Fuel Efficiency Standards in the U.S.," Journal of Industrial Economics, Volume 46, Pages 1-33.

Görg, H. and F. Warzynski, 2006. "The Dynamics of Price Cost Margins: Evidence from UK Manufacturing," *Revue de l'OFCE*, Volume 97 bis, Issue 5, Pages 303-318.

Hall, R., 1988. "The Relation between Price and Marginal Cost in U.S. Industry," *Journal of Political Economy*, Volume 96, Pages 921-947.

Hausman, J., G. Léonard and J.D. Zona, 1994. "Competitive Analysis with differentiated goods," Annales d'Economie et de Statistique, Issue 34, Pages 159-180.

Hausman, J.A., 1979. "Individual Discount Rates and the Purchase and Utilization of Energy-using Durables," *The Bell Journal of Economics*, Volume 10, Issue 1, Pages 33–54.Houde, S., 2014a. "How Consumers

Respond to Environmental Certification and the Value of Energy Information," *NBER Working Paper No. 20019*.

Houde, S., 2014b. "Bunching with the Stars: How Firms Respond to Environmental Certification," Unpublished manuscript.

International Energy Agency (IEA) 2007. *Mind the Gap. Quantifying Principal-Agent Problems in Energy Efficiency.*

Jacobsen, M., 2013. "Evaluating U.S. Fuel Economy Standards in a Model with Producer and Household Heterogeneity," American Economic Journal: Economic Policy, Vol. 5, No. 2, 2013.

Jaffe, A.B. and R.N. Stavins, 1994. "The Energy-Efficiency Gap: What Does it Mean?" *Energy Policy*, Volume 22, Issue 10, pages 804–10.

Lees, E.W., 2008. *Evaluation of the Energy Efficiency Commitment 2005-05.* Report to DECC, Eoin Lees Energy.

Li, S., Timmins, C. and R.H. von Haefen, 2009. "How Do Gasoline Prices Affect Fleet Fuel Economy?" *American Economic Journal: Economic Policy*, Volume 1, Issue 2, Pages 113 – 37.

McFadden, D., 1973. "Conditional Logit Analysis of Qualitative Choice Behavior," in P. Zarembka (ed.), *Frontiers in Econometrics*, Pages 105–142.

McRae, D., 1980. "Rational Models for Consumer Energy Conservation," in Burby and Marsden (eds.), *Energy and Housing*, Oelgeschleger, Gunn and Hain, Publishers, Inc. Cambridge, MA.

Meier, A.K. and J. Whittier, 1983. "Consumer discount rates implied by purchases of energy-efficient refrigerators," *Energy*, Volume 8, Issue 12, Pages 957–962.

Müller, H., Kroll, E.B. and B. Vogt, 2012. "Do real payments really matter? A re-examination of the compromise effect in hypothetical and binding choice settings," *Marketing Letters*, Volume 23, Issue 1, Pages 73–92.

Office for National Statistics, 2013. *Consumer Price Inflation Time Series Dataset*, September 2013.

Purple Market Research, 2007. Trade Sector Profiles: White Goods Sector.

Rapson, D., 2014. "Durable goods and long-run electricity demand: Evidence from air conditioner purchase behavior", *Journal of Environmental Economics and Management*, Volume 68, Issue 1, Pages 141-160.

(http://www.sciencedirect.com/science/article/pii/S0095069614000217)

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Revelt, D. and K. Train. 1998. "Mixed Logit with Repeated Choices: Households' Choices of Appliance Efficiency Level," *The Review of Economics and Statistics*, Volume 80, Issue 4, Pages 647–657.

Roeger, W., 1995. “Can Imperfect Competition Explain the Difference between Primal and Dual Productivity Measures? Estimates for US Manufacturing,” *Journal of Political Economy*, Volume 103, Issue 2, Pages 316–330.

Ryan, L., Moarif, S., Levina, E. and R. Baron, 2011. “Energy Efficiency and Carbon Pricing the Gap. Energy Efficiency Series,” *Information Paper*. International Energy Agency.

Simonson, I. and A. Tversky, 1992. “Choice in Context: Tradeoff Contrast and Extremeness Aversion,” *Journal of Marketing Research*, Volume 29, Issue 3, Pages 281–295.

Spurlock, Anna C. (2014) The Implications of Market Structure for Appliance Energy Efficiency Regulation. Working paper. http://ageconsearch.umn.edu//handle/180235

Tsvetanov, T. and K. Segerson, 2014. ”The Welfare Effects of Energy Efficiency Standards When Choice Sets Matter,” *Journal of the Association of Environmental and Resource Economists*, Volume 1, Issue 1/2, Pages 233-271.

US Department of Energy (DOE), 2009. *ENERGY STAR Refrigerator Market Profile*. http://apps1.eere.energy.gov/states/pdfs/ref_market_profile.pdf. Accessed: 2 July, 2015.

US Department of Energy, 2006. *Energy Conservation Standards Activities.*

Verboven, F., 2002. “Quality-Based Price Discrimination and Tax Incidence: Evidence from Gasoline and Diesel Cars,” *RAND Journal of Economics*, Volume 33, Issue 2, Pages 275–297

Wooldridge, J.M., 2005. “Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity,” *Journal of Applied Econometrics*, Volume 20, Issue 1, Pages 39–54.

Appendices

A-H are the main appendices. I-O includes elements for online publication.

A: 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 A.1. The estimate of γ varies across specifications, but remains below 1.

Table A.1: First difference GMM estimation results of sales with alternative nests

Dependent variable: log. market share of product j				
Nests based on:				
refrigerators vs. refrigerator-freezers	No	Yes	Yes	No
Above/below median capacity	No	Yes	No	Yes
Built-in/freestanding	No	No	Yes	Yes
Importance of total electricity costs (γ)	0.7248** (2.26)	0.6455*** (4.11)	0.2695 (1.25)	0.6877*** (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	0.8587*** (17.81)	1.075*** (25.32)	0.8932*** (16.71)
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.

B: 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 B.1). 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 next, 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 of the observations of product j between 2002 and 2007, and correspond to the average of all of the sales registered by product j between 2002 and 2007.

Table B.1: Hedonic regressions to construct the instruments (freezers and washing machines)

Dependent variable	Price of washing machines	Price of built-in freezers	Price of freestanding freezers
By year, by category of appliance fixed effects			
Small, 2002	0	0	-18.8481 (-0.46)
Small, 2003	-42.5061*** (-3.11)	-2.5749 (-0.12)	-18.4543 (-0.42)
Small, 2004	-75.2039*** (-2.85)	-11.508 (-0.31)	-5.8397 (-0.11)
Small, 2005	-125.6751*** (-3.18)	-16.0016 (-0.29)	-7.9437 (-0.13)
Small, 2006	-159.7466*** (-3.05)	-43.4277 (-0.6)	15.2585 (0.2)
Small, 2007	-205.2927*** (-3.13)	-38.6044 (-0.45)	19.0729 (0.21)
Large, 2002	37.824 (1.45)	10.3909 (0.24)	8.3791 (0.28)
Large, 2003	-3.9397 (-0.12)	1.2222 (0.03)	-2.8049 (-0.08)
Large, 2004	-57.4207 (-1.59)	13.543 (0.31)	9.7592 (0.21)
Large, 2005	-128.0074*** (-2.94)	4.5595 (0.08)	17.6663 (0.3)
Large, 2006	-174.3192*** (-3.18)	12.0702 (0.17)	27.5309 (0.38)
Large, 2007	-218.5002*** (-3.24)	-14.9726 (-0.18)	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.

C: 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 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 C.1, which corresponds to the fit of various ARIMA specifications for the price expectations in 2007.[30]

Table C.1: 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).

[30] ARIMA models in table 18 only include lags at $t - 1$. We tested for the inclusion of more lags but these models do not fit the data as well as this specification. Either 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 modelled.

2. Results of the 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 C.2 presents the results of each ARIMA model used to produce price expectations for purchases that take place in 2002, 2003, 2004, 2005, 2006 and 2007.

Table C.2: 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).

The figure below plots the predicted prices obtained for each year of the forecast. In general, the output of the forecast is close to a random walk, with a tendency to return to the average of the previous years.

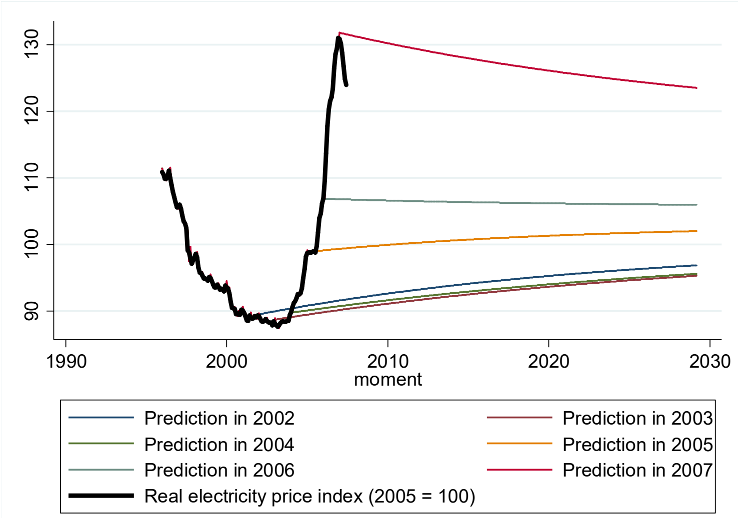

Figure C.1: Expected electricity prices as forecasted with the ARIMA model (2005 = 100)

D: 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 refrigerator-freezers). Table D.1 presents the results where the lifetimes of both kinds of appliances are assumed to be 20% higher and lower. It shows that changes in our assumption have a limited impact on the results. This is mostly because operating costs are discounted: electricity consumption over 10-15 years is given a low weight in any case.

Table D.1: 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 refrigerator-freezers	17.5	14	21
Independent variables			

Dependent variable: log. market share of product j			
Importance of total electricity costs (γ)	0.6538*** (4.32)	0.742*** (4.33)	0.5974*** (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	0.8889*** (16.14)	0.889*** (16.12)	0.8889*** (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. 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 it was not constant. In Table D.2, 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 D.2 shows consumer myopia would be reduced, as consumers would underestimate energy costs by 27%.

Table D.2: First difference IV-GMM estimation results of the sales equation, where expected electricity prices are estimated using time-varying marginal prices

Independent variables	

Independent variables	
Importance of total electricity costs (γ)	0.7346*** (4.32)
Utility for money (α)	0.0052*** (3.51)
Within-group correlation of error term (σ) for the demand equation	0.8889*** (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 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.

E: 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 varied significantly over the study period.

Results for the sales equations show limited differences with the results obtained in the base specification.

Table E.1: First difference IV-GMM estimation results of the sales equation, with instrumentation of the operating costs

Independent variables	
Importance of total electricity costs (γ)	0.5676***

Independent variables	
	(3.53)
Utility for money (α)	0.0051***
	(3.48)
Within-group correlation of error term (σ) for the demand equation	0.8888***
	(16.37)
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.

F: Estimation method for the average markup

Markup estimation

The calibration of individual markups is done in reference to an average markup of 19.6%. We consider that any product j below a given sales level M has a markup equal to 0 due to lack of market power. Beyond M, the markup increases with product j's market share in the proportions estimated with Eq. (7). We choose the value of M such that the sales-weighted average markup equals 19.6%.[31] In addition, we put an upper bound on estimated markups at the 99% percentile to ensure that the simulation results are not driven by outliers.

The method used to estimate the average markup is the following. Roger (1995) shows that markups can be estimated from the difference between the Solow residual (SR_t) and the price-based Solow residual (SRP_t):

$$SR_t - SRP_t = B\Delta x_t + u_t$$

[31] . Below 77 sales, the markup is assumed to be zero and then increases in line with Eq. (7).

With $\Delta x_t = (\Delta y_t - \Delta k_t) - (\Delta p_t - \Delta r_t)$. Δy_t , Δk_t , Δp_t and Δr_t are respectively the log differences in output, capital, the price of output and the cost of capital. u_t is an error term. The coefficient B is directly related to the markup μ such that: $\mu = 1/(1 - B)$. Görg and Warzynski (2006) adapt Roeger's equation to the standard financial information provided by firms. We follow their methodology and estimate:

$$\Delta \log(OR_t) = \alpha_1 \Delta \log(CGS_t) + \alpha_3(\Delta \log(NK_t) + \log(R_t)) + B\big(\Delta \log(OR_t) - (\Delta \log(NK_t) + \log(R_t))\big)$$

OR_t is the operating revenue, CGS_t is the cost of goods sold, NK_t tangible assets and R_t the firm-specific cost of capital, such that:

$$R_t = P_{K,t} \frac{r_t + \delta_t}{1 - \tau_t}$$

With $P_{K,t}$the index of investment good prices, r_t the real interest rate, δ_t the depreciation rate and τ_t the corporate tax rate.[32]

With this methodology in mind, we gather financial data for a panel of UK firms operating in two sectors: a) the manufacture of electrical equipment; and b) the retail sale of electrical household appliances in specialized stores. The data was extracted from the ORBIS Database and was available for 2006-2015.

We calibrate R_t using the UK consumer price index for $P_{K,t}$ since we lack an investment price index. We calculate r_t based on the Bank of England weighted-average interest rate of time deposits with fixed original maturity above one year from private non-financial corporations. We subtract the inflation rate from this to obtain a real interest rate. The depreciation rate is

[32] Görg and Warzynski (2006) include the cost of employees and the cost of materials in their equation instead of the cost of sold goods. We have adapted their equation due to data constraints. However, the cost of sold goods mostly consists in the cost of materials and the cost of labor directly used to produce the goods.

calculated for each firm based on declared depreciation and amortization losses.

As for the estimation *per se*, we consider that the error component term of our regression includes a firm-specific fixed effect and therefore estimate the equation above with demeaning instead of standard OLS. In addition, the data we use is for 2006-2015 whereas we are interested in the markups for 2002-2007. Therefore, we need to investigate whether B might have evolved over time, due to changes in competition intensity. This is done in additional specifications where we assume $B \equiv B_0 + B_1 t$. The estimation results are provided in Table F.1, separately for both sectors.

Table F.1: Fixed effect markup estimation

Independent variables	Manufacturing sector		Retail sector	
Log difference in cost of goods sold	0.5883*** (12.69)	0.5682*** (11.99)	0.6792*** (12.20)	0.6678*** (13.34)
Log difference in tangible assets plus cost of capital	-0.0256 (-1.21)	-0.0002 (-0.01)	0.0082 (0.82)	0.0144 (1.07)
B (or B_0)	0.0796*** (3.26)	0.1897* (1.90)	0.0371*** (3.23)	0.0890*** (3.11)
B_1		-0.0213 (-1.39)		-0.0099** (2.31)
Year dummies	Yes	Yes	Yes	Yes
Observations	2,703	2,703	536	536

Notes. Dependent variable is log difference of operating revenue. Standard errors are clustered at firm level.

We find a value of B equal to 8.0% in the manufacturing sector, with no evidence of increased or decreased competition over time. The corresponding markup is 8.6% (95% confidence interval is 3.0-14.3%). On the other hand, we find evidence of decreasing competition in the retail sector (B_1 statistically significant at 5%). If we extrapolate the value of B in the retail sector for 2002-2007 based on the estimates of B_0 and B_1, we obtain a value of 9.9%. The corresponding markup is 11.0% (95% confidence interval is 3.1-18.9%).

Adding the two markups for the manufacture and retail of electric appliances gives an average markup of 19.6%, with a 95% confidence interval of 9.9%-

29.3%. The average estimate of 19.6% is the one we use as our base value in the welfare evaluation.

G: Sensitiveness analysis of simulations

We perform a sensitiveness analysis of our simulations with the lower (9.9%) and upper (29.3%) values of the 95% confidence interval of our average markup estimate. The results of the welfare evaluation are globally similar, even though the magnitude of imperfect competition (and with it the average profits cut down under perfect competition) changes.

Table G.1: Simulated impacts of myopia and imperfect competition on the energy consumption with different average markups

	Energy consumption (kWh/year)	
	Markup of 9.9%	Markup of 29.3%
Observed situation	310.2	310.2
Non-myopic consumers	281.6	283.6
Perfect competition (zero mark-ups)	316.1	330.6
Perfect competition and non-myopic consumers	282.4	293.9

Table G.2: Welfare impacts of myopia and imperfect competition with different average markups

Welfare impacts *	Consumer surplus	Average profit	Welfare
Markup of 9.9%			
Withdrawing myopia	+24.1	-11.4	+12.8
Perfect competition	+34.7	-29.3	+5.4
Both	+49.1	-29.3	+19.8
Markup of 29.3%			
Withdrawing myopia	+26.5	-18.4	+8.1
Perfect competition	+109.2	-86.4	+22.8
Both	+113.6	-86.4	+27.1

*: unit is 2005 pounds. Values are for an average sale. When myopia prevails, we have subtracted unforeseen energy costs from the consumer surplus. The sales-weighted average price of products included in the welfare evaluation is 296 pounds.

H: Modifications to the set of controls used in the supply equation

The regression below increases the stringency of the controls used in the supply equation. We first introduce fully interacted fixed effects: by-nest by-brand by-year fixed effects. Results lose some precision but are unchanged compared to our baseline specification.

Table H.1: Fixed effects 2SLS Estimation results for the price equation with fully interacted fixed effects

Dependent variable	Log. price of product *j*
Markup, η	0.0759* (1.79)
Year x nest dummies x brand dummies	Yes
Product fixed effects	Yes
Weak identification test	
Kleibergen-Paap rk Wald F statistic	12.13
Max. IV bias	10-15%
Observations	2,421

Notes. *t*-statistics are 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.

Another possibility is to introduce nest-specific or brand-specific quadratic trends. Likewise, results are quite similar in magnitude.

Table H.2: Fixed effects 2SLS Estimation results for the price equation with nest-specific quadratic interactions between height and time

Dependent variable	Log. price of product *j*	Log. price of product *j*
Markup, η	0.0438** (2.40)	0.0818*** (2.60)
Year x nest dummies	Yes	Yes
Year x brand dummies	Yes	Yes
Nest-specific quadratic interactions between height and time	Yes	No
Brand-specific quadratic interactions between height and time	No	Yes
Product fixed effects	Yes	Yes
Weak identification test		
Kleibergen-Paap rk Wald F statistic	29.95	14.07
Max. IV bias	<10%	10-15%
Observations	2,421	2,421

Notes. *t*-statistics are 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.