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BY

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Can Energy Efficiency Standards Reduce Prices and Improve Quality? Evidence from the US Clothes Washer Market

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Abstract

We examine the effect of energy efficiency standards on the clothes washers market using a constant-quality price index constructed from same-model price changes for a significant majority of clothes washer models sold in the United States between 2001 and 2011. We find constant-quality prices fell over time, while quality increased, particularly around times energy standards changed. We estimate total welfare changes by assuming the difference between average price and constant-quality price indicates average quality. Further examination shows product entry and exit are associated with changes federal standard for energy efficiency. With policy changes implicitly coordinating entry and exit, average vintage sharply falls when standards change. Controlling for individual model and time effects, we find that lower average vintage is associated with more rapidly falling prices, an effect we attribute to increased competition. We also find a strong relationship between clothes washer prices and average vintage of the same manufacturer, which indicates cannibalism explains much of the declining price of clothes washers over time. We apply the same methodology to other appliances (clothes dryer, room air conditioners and refrigerators) which did not experience simultaneous efficiency standard changes between 2001 and 2011. We see the same cannibalism in the market for clothes dryers, but not for room air conditioners or refrigerators. We also find notable improvements both in the characteristics of clothes washers that directly improve energy efficiency and those that promote convenience and space-saving. Energy efficiency standards appear to facilitate more rapid innovation and price declines.

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1 Introduction

In recent years, a number of actual and proposed energy efficiency standards proliferated in the US energy-using durable goods markets. For automobiles, the Corporate Average Fuel Economy (CAFE) mandates that a manufacturer's annual fleet of vehicles to have an average fuel economy of 31 miles per gallon (mpg), with gradual increases to 35 mpg by 2016. Household appliances are also subject to Energy-Star certifications—a voluntary labeling program implemented by the Environmental Protection Administration (EPA) and the Department of Energy (DOE) to identify and promote products that are sufficiently more efficient than the federal standards. Some states have also adopted energy efficiency standards for newly constructed and renovated buildings, while the federal government implements Energy-Star certification for energy-efficient homes.

Many see energy efficiency as the least-cost way to reduce greenhouse gas emissions (GHG). For example, the widely-cited report by McKinsey & Company (Nauclér and Enkvist, 2009) estimates that the cost of abating about a third of global GHG emissions is *negative*. More fuel-efficient car engines, LED lightbulbs, more energy-efficient appliances, and better-insulated buildings are just a few of these technologies. Based on these engineering-based estimates, which some may justifiably question (Allcott and Greenstone, 2012), it appears that to a significant extent reducing pollution and slowing climate change is a free lunch. Quite aside from externalities, standards may be justified, at least in part, by behavioral anomalies that inhibit people from taking full advantage of potential efficiency gains.

Given net economic benefits, it is puzzling why consumers and businesses seemingly underinvest in energy efficiency. The conundrum over consumers' apparent discounting of future energy savings dates back to early hedonic modeling (Hausman, 1979) and consumer choices that relate purchase decisions to product prices, energy efficiency, and other product attributes (Train, 1985), and had been called *energy paradox* (Jaffe and Stavins, 1994a) or *energy efficiency gap* (Jaffe and Stavins, 1994b). Economists typically explain this phenomenon by pointing to information problems and/or bounded-rational behavior. The energy-efficiency component of a durable good purchase is typically small, so a boundedly-rational consumer will focus more on the observable and salient characteristics of the product, and less on energy efficiency (Allcott et al., 2014). Manufacturers realize that uninformed or boundedly-rational consumers are unwilling to pay the full net present value of improved efficiency, and thus provide less efficient products in the market. Public good attributes of innovations pertaining to energy efficiency could exacerbate the problem. There is also the *landlord-tenant* agency problem; that is, imperfectly informed renters may not be willing to pay for energy-efficient apartments; thus reducing the incentive for landlords to invest in energy efficiency (Davis, 2011). Others point out that various search costs and high borrowing costs might explain why energy efficiency gap exists (Parry et al., 2014).

Not all scholars are convinced that the energy efficiency gap is large or important. For example, Hassett and Metcalf (1993) argue that the gap arises due consumers aversion toward partially irreversible investment with uncertain returns. Consumers' option values might create higher thresholds for investment in more efficient products than implied by net-present-value criteria. Meanwhile, Allcott and Greenstone (2012) regard earlier empirical researches as "not meeting modern standards of credibility." Earlier research mainly examined cross-sectional relationships between prices and product attributes, which might be confounded by missing variables. However, some more recent research with modern research designs suggests the gap still exists and is large.

Even if we accept that the energy efficiency gap reflects a market failure, existence of the gap itself does not necessarily imply that efficiency standards are an efficient means of correcting it. More pragmatic questions may pertain to the consequences of the standards, like how costly they are to businesses and consumers, how strict they ought to be if already selected as a policy tool, and whether and to what extent standards actually reduce energy consumption. Some have investigated the impact of more stringent standards in the context of markets with quality differentiated goods (see for example, Ronnen (1991); Crampes and Hollander (1995); and Valletti (2000)). A number of empirical studies looking at this issue can be found in the automobile market (Goldberg, 1998; Jacobsen, 2013; Sallee, 2013). For household appliances, Chen et al. (2013) and Spurlock (2013) provided empirical evidence showing the correlation between imposing energy efficiency standards and, surprisingly, *declining prices* of durable goods. However, the mechanism through which these standards influence price remains unclear.

In this study, we follow this later literature, evaluating how more stringent energy efficiency standards affect price and quality of washing machines using panel, point-of sale data for a near population of models. We add to existing literature in three ways: (1) by disentangling quality changes from price changes; (2) by developing a consumer welfare measure that accounts for changes in prices and qualities, and linking these changes to policy changes; and (3) by considering a mechanism through which energy efficiency standards influence price, quality, and consumer welfare.

The first two contributions are anchored on formulation of a Constant Quality Price Index (CQPI). Given unobserved heterogeneity of washer models sold over time, the CQPI provides a more accurate measure of price changes by looking at price changes of continuing models that were sold across multiple periods. Given an index for constant-quality prices, and assuming that, looking across models at a given point in time, prices increase monotonically with quality, we develop a quality index linked to the difference between average price and the CQPI. Changes in the CQPI implicitly account for changes in the price of quality, which facilitates estimates of the total welfare change under quasi-linear utility. We then examine how price, quality and total welfare change with changes in the federal minimum energy efficiency (ME) standards and Energy Star (ES) thresholds for clothes washers. Finally, we show evidence that the policy-induced changes in price, quality and welfare are connected to entry and exit of models. In particular, we find that price changes are more closely connected to own-brand competition (cannibalism) as opposed to entry and exit of models by competing brands.

2 Policy Background

The United States initiated the first national appliance standard with the passage of the National Appliance Energy Conservation Act (NAECA) in 1987. The law established the initial minimum energy efficiency standard for a set of appliances sold in the US and directed the Department of Energy (DOE) to periodically update the standards. Subsequent legislation, such as the Energy Policy Act (EPAct) of 1992, the EPAct of 2005 and the Energy Independence and Security Act (EISA) of 2007, included additional products. Stipulations from these laws were based on consensus agreements between manufacturers and energy efficiency advocates (Gold et al., 2011).

Clothes washers were among the initial appliances subjected to minimum energy efficiency standards under the 1987 NAECA. The first standard took effect in 1988. DOE updated the standard in 1990 and implemented it in 1994. In 2001, DOE adopted a new standard that was implemented into two phases. The first phase revised the basis for the energy minimum efficiency standard from the traditional energy factor (EF) to the modified energy factor (MEF). While both are measured in terms of cubic feet per kilowatt-hour (kWh) cycle, the MEF includes the energy required for drying. Washers with faster spin cycles remove more moisture before drying, thereby saving energy. The higher the EF or the MEF, the more efficient the product. The second phase increases the MEF by more than 20% from its 2004 level. In 2007, DOE updated the standard to include a maximum water factor (WF) requirement. WF measures the ratio of the quantity of water used in one cycle to the capacity of the washer. A lower WF increases MEF, mainly to account for energy saved from heating water. The updated standard was implemented in 2011. Clothes washers are also part of the Energy Star (ES) program. ES is a voluntary program that identifies and promotes energy efficiency through labeling of products that exceed minimum standards by a certain threshold. Since 1997, sales growth of ES-certified clothes washers exceeded that of the overall market (D&R International, Ltd., 2008).

In 2001, ES certification adopted MEF as a measure of energy efficiency. The threshold was updated in 2004, increasing the required MEF level from 1.26 to 1.42. In 2007, the Department of Energy increased MEF level another 21% and also included the water factor (WF). In July 2009 certification requirement increased the ES threshold efficiency by 5% and reduced WF by more than 6% percent. In March 2008, the Department of Energy updated the July 2009 standard with additional requirements that went into effect in January 2011. The 2011 threshold improves energy and water efficiency level by an additional 10% and 20% over 2009 levels, respectively. Table (1) summarizes the minimum energy efficiency and Energy Star standards adopted and implemented between 1991 and 2011.

Table 1: US Federal Minimum Standards and Energy Star Standards for Residential Clothes Washers, 1991-2011

Date Adopted	Date Effective	Federal Minimum Standard	Energy Star Standard
1991	1994	EF $\geq$ 1.18	-
1997	2001	-	MEF $\geq$ 1.26
2001	2004	MEF $\geq$ 1.04	MEF $\geq$ 1.42
2001	2007	MEF $\geq$ 1.26	MEF $\geq$ 1.72
		-	WF $\leq$ 8.0
2009	2009	-	MEF $\geq$ 1.8
		-	WF $\leq$ 7.5
2007	2011	MEF $\geq$ 1.26	MEF $\geq$ 2.0
		WF $\leq$9.5	WF $\leq$ 6.0

Notes: The table shows the adoption and implementation years of federal minimum standards and energy-star standards from 1991 to 2011 for residential standard clothes washers. The standards are set based on the Modified Energy Factor (MEF), the Energy Factor (EF) and the Water Factor (EF). The Department of Energy defines (i) MEF as the ratio of the capacity of the washer to the energy used in one cycle; (ii) EF as the MEF excluding the energy for drying clothes; and (iii) WF as the quantity of water used in one cycle per unit capacity of the washer. The table does not include standards adopted and implemented for non-residential and compact (capacity less than 1.6 cubic feet) type of clothes washers.

Source: Department of Energy

3 Data

We use point-of-sale data for clothes washers, clothes dryers, room air conditioners, and refrigerators from the NPD Group, purchased by Lawrence Berkeley National Laboratory. The data were collected from a set of US retailers and are aggregated at the national level.[1] The data contain monthly total revenue and total quantity sold by individual model number from January 2001 to December 2011. We calculated the unit price by dividing total revenue by total units sold in each month. We can interpret this price variable as average revenue, which includes in-store discounts for individual clothes washers, but not mail-in rebates. To check how our price variable represents the actual selling price of individual clothes washer, we randomly selected 30 models. We verified the manufacturer's suggested retail price (MSRP) of these models online and find that our price variable is 20% less on average, which seems reasonable given the time since NPD collected the data.

[1]NPD group was unable to provide subnational aggregations.

We drop observations with prices falling below $100, as these observations are outliers and appear unrealistic. Remaining models comprise 99.9% of total revenue. About 35% of the observations have masked model numbers to preserve the anonymity of NPD Group's partner retailers. NPD assigned these models alternative codes, but it is possible that the models may in fact be the same as others in the data set. Because these masked model numbers may not be new when each is first observed in the data, we compute separate statistics with and without masked models to check the robustness of our findings.[2] Summary statistics are reported in Table (2).

Table 2: Summary Statistics

	Baseline Data (1)	No Masked Models (2)
Price ($)	650.55	700.09
	(355.92)	(348.89)
Sales (units)	744.00	872.30
	(1,908.47)	(2,007.55)
Revenue ('000$)	382.40	481.45
	(966.37)	(111.02)
Share of Front Loaders	38.90	42,85
Share of Energy Star Qualified	48.53	44.28
No. of models	2,733	1,245
Observations	38,504	24,838

Note: The table shows the monthly average price, sales and revenues generated between 2001 and 2011 for the sampled clothes washers for each of the dataset: (1) Baseline Data treats all model numbers (including masked) as unique models, and (2) No Masked drops the masked models. We also included the share of front loaders and Energy Star qualified units, as well as the number of models for each dataset. Observations with prices falling below $100 were dropped as these observations are outliers and appear to be unrealistic.

Sources: The NPD Group, authors' calculations.

4 Price Trend of Clothes Washer Over Time

We calculate average price by simply dividing total revenue in each month by total units sold (panel (a) of Figure 1). The trend is slightly up from 2001 through 2006, then falls slightly through 2008, and then rises again through 2010, and then falls sharply in the latter part of the data. These changes in average price include changes in the mix of models sold as well as quality changes, as models enter and exit the marketplace. Changes in mix and overall quality may be driven

[2] See Appendix B for the results of the robustness check.

by technological advance, income growth or decline, standards, or other factors affecting demand, production costs, or competition.

To measure how prices for a fixed quality of washers has changed over time, we construct a price index that holds quality constant. We call this index the constant quality price index or CQPI. The CQPI is based on the percentage changes in price, p_{it}, of a specific model i for two consecutive time periods within its shelf life, weighted by average units sold, q_{it}, in these periods. In cases where a model's lifetime overlaps with another, we take the average price change of these models and weight it by units sold (see equation 1). The index explicitly excludes new models and exiting models, because these differences over time cannot be calculated. Panel (b) of Figure 1 shows the trend of the constructed monthly CQPI between 2001 and 2011. Holding quality constant, the price of an average clothes washer goes down by an average of 0.9% each month, which translates to an annualized deflation of about 11.23%.

$$\text{CQPI}_t = \text{CQPI}_{t-1}\left(1 + \frac{2\sum_i W_{it}\left(\frac{p_{it}-p_{it-1}}{p_{it}+p_{it-1}}\right)}{\sum_i W_{it}}\right),\ \forall t > 0 \tag{1}$$

where

$$\text{CQPI}_0 = \frac{\sum_i q_{i0}p_{i0}}{\sum_i q_{i0}}$$

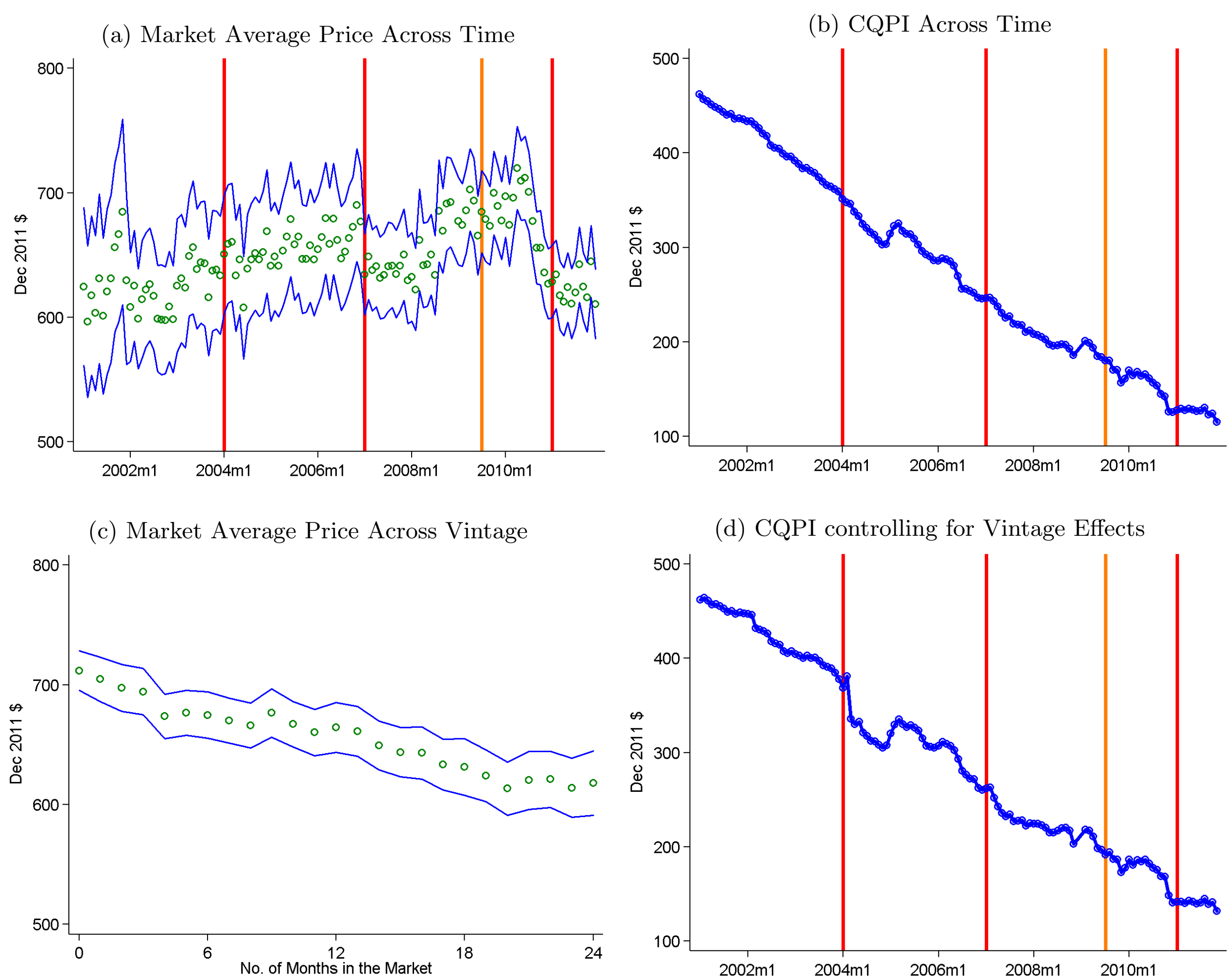
and

$$W_{it} = \frac{q_{it} + q_{it-1}}{2}, \forall i \text{ that exist in } t \;\&\; t-1.$$

One concern about the CQPI is that the weights are endogenous. Consumers may substitute toward products with lower prices, causing a bias in the overall trend. If we weight price changes by the initial period of the difference, the bias would most likely be positive, as models discounted in the initial period would presumably rise in price and be weighted more heavily. Conversely, if we were to weight by the second period then models discounted in the second period would presumably see a larger price decline while sales increased, biasing the overall trend downward. We therefore weight the two periods equally. Note, however, that weighting by the initial or second period sales has no noticeable influence on the CQPI. Appendix 14 reports these alternative constructions.

Panel (c) shows that average price of clothes washers declines across the product's vintage (months since first introduction). Clothes washers appear to have lower prices as the product

Figure 1: Market Average Price and CQPI Trends



Notes: Panel (a) shows sales-weighted average prices and 95% confidence band in blue. Panel (b) shows the constant quality price index (CQPI). Panel (c) shows average price in relation to product vintage, defined as months since the model number first appeared in the data. Panel (d) shows the CQPI adjusted for product vintage, estimated from a fixed effects regression model. The solid red vertical line represents the effective date of simultaneous policy changes in the federal minimum energy efficiency standard and Energy Star certification threshold, while the orange vertical line is for the Energy Star threshold change that took effect in July 2009. All prices are in December 2011 US dollars.

ages, typically declining by more than 10% after a year. The trend of high introductory price and declining price as product ages can be due to several factors. Through learning-by-doing, the firm's costs may decline over time. Alternatively, firms may need to lower prices as newer competition products are introduced. Relatedly, firm's may use intertemporal price discrimination to extract rents from consumers with different demands for the latest technology (Stokey, 1979). This kind of price discrimination may be more acute for goods with status or fashion values, like cars or perhaps more visible appliances like refrigerators (Stamminger et al., 2005). Intertemporal price discrimination can occur if there is sufficiently rapid technological advance, so that the latest models have sufficiently higher quality than earlier vintages, and different buyers have different willingness to pay for quality. And if the user value of having the appliance in a timely manner is sufficiently high, as is likely in the case of a clothes washers, it's easy to see why many buyers would be unwilling to wait for price to fall or quality to rise.

Unless declining production costs explain the price pattern with respect to vintage, which seems unlikely given the magnitude, the pattern itself suggests competition is imperfect. Presumably imperfectly competitive firms would strategically time product entry, staggering introduction of new products so as to maximize potential novelty. Although we don't attempt to model it formally, we expect that, in the absence of policy or other interventions, equilibrium product introductions would be spread out over time, akin to spatial models of product diversification in monopolistic competition. Many kinds of events could disrupt equilibrium timing of product entry. Because prices are influenced by vintage, and via competition are likely connected to vintages of competing models, it is plausible that changes in standards may affect pricing patterns via the rate and timing of product introductions. We return to this issue below.

For now we focus on how vintage influences CQPI. If product entries were uniform over time, the distribution of product vintages would be constant, and CQPI would be unaffected. If the distribution of vintages shifts lower or higher, this would decelerate or accelerate the decline in the CQPI, respectively. The data show this distribution does in fact shift periodically. We control for this effect by estimating a regression of model prices against vintage fixed effects, model fixed effects, and time fixed effects. The model is:

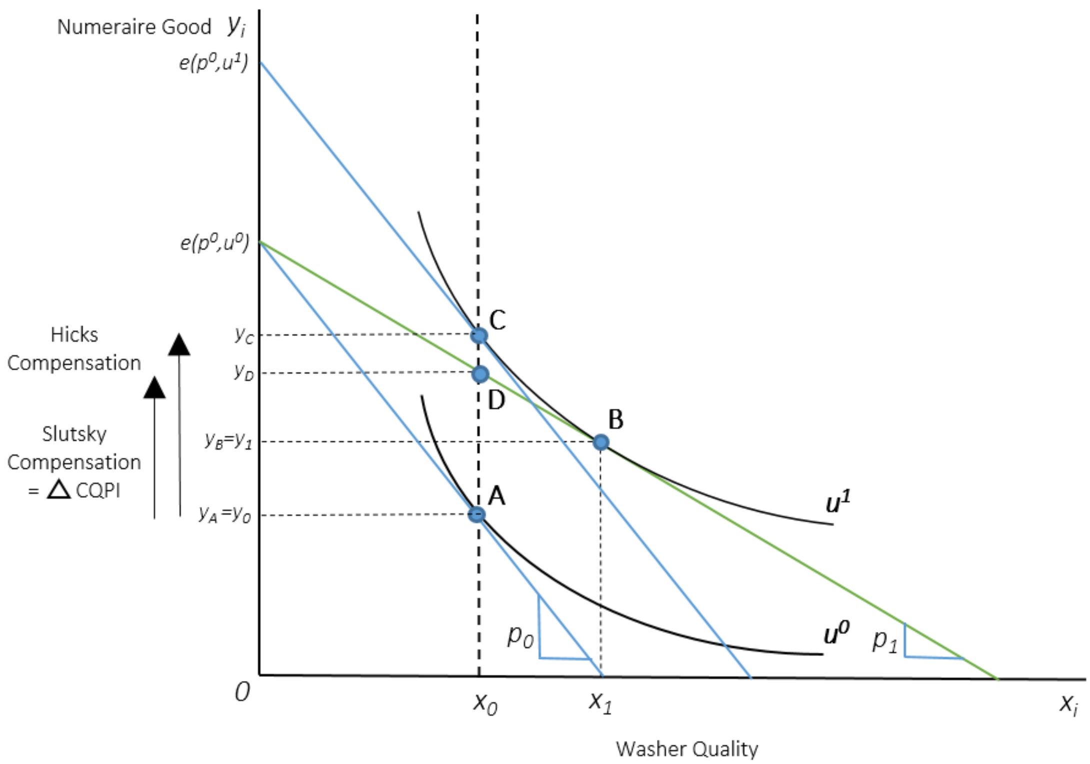
$$p_{it} = \alpha_i + v_k + \gamma_t + \varepsilon_{it}, \tag{2}$$

where p_{it} denotes the price of model i at time t, α_i is a model fixed effect, v_k is vintage fixed effect for vintages $k \in \{2, ..99\}$ representing periods since first introduction, γ_t is a time period fixed effect, and ε_{it} is the error. Because the CQPI excludes entering and exiting models, the regression also excludes them, so vintage starts with a value of two instead of one. To adjust the CQPI for vintage effects, we take the sales-weighted average of the vintage fixed effect in each time period and deduct it from the CQPI. Panel (d) in Figure 1 shows the CQPI adjusted for the product's vintage fixed effect. While the trend generally exhibits a downward sloping pattern similar to the unadjusted CQPI, it is somewhat less smooth. Of particular interest in this figure is the visible discontinuous drop in the price of clothes washers around the policy change in 2004.

5 Welfare Implications of the Price Change

In this section we consider the welfare change from declining clothes washer prices. We use a simple framework that assumes an individual will buy a washer, but must choose a level of quality. Higher quality washers are more expensive and the price of quality is relative. Income not spent on washer quality can be spent on other goods and services. As washer prices fall, the budget constraint pivots out, allowing the consumer to buy higher quality washer while spending less (Figure 2). The figure shows standard constrained consumer choice, with washer quality on the horizontal axis and the numeraire (real dollars) on the vertical axis. As washer prices fall, the consumer's choice moves from point A to point B on the graph.

Figure 2: Welfare Implications of a Price Fall of Clothes Washers.



We estimate welfare changes using standard Hicksian compensation, the income needed to achieve utility u_1 had prices not fallen, represented by the vertical distance between point A to point C in Figure 2, which we denote ΔW. We can estimate the welfare improvement by assuming a quasi-linear form for a representative consumer's utility function u. Given total consumption of quality x and the consumption of numeraire y, utility is $u(x, y) = v(x) + y$ where $v' > 0$ and $v'' < 0$. This specification assumes zero income elasticity of demand for x_i, which is reasonable as washer purchases account for a small share of representative buyer's lifetime income. For simplicity and tractability, we use a quadratic approximation.

$$v(x) = ax - \frac{b}{2}x^2$$

We can define ΔW as;

$$\Delta W = e(p^0, u^1) - e(p^0, u^0) \tag{3}$$

where $e(p, u)$ describes the minimum amount of money the consumer needs to achieve utility level u at price p. Thus, $e(p^0, u^1)$ and $e(p^0, u^0)$ correspond to the downward sloping blue lines intersecting points C and A, respectively, in Figure 2. Because $e(p^0, u^0) = e(p^1, u^1)$,

$$\begin{aligned} \Delta W = & \quad e(p^0, u^1) - e(p^1, u^1) \\ = & \quad \int_{p_1}^{p_0} h(p, u^1)\, dp, \end{aligned} \tag{4}$$

where $h(p, u^1)$ is the Hicksian (compensated) demand curve, which comes from the consumer's cost minimization problem,

$$\min_{x \geq 0, y \geq 0} px + y$$

$$\text{s.t.} \quad ax - \frac{b}{2}x^2 + y \geq u$$

which gives,

$$x^* = \frac{a - p}{b}$$

The change in welfare is thus

$$\begin{aligned} \Delta W &= \int_{p_1}^{p_0} \frac{a - p}{b} dp \\ &= \frac{a(p_0 - p_1)}{b} - \frac{p_0^2 - p_1^2}{2b} \end{aligned} \tag{5}$$

Note that because utility is quasi-linear, the Marshallian and compensated demand curves are identical. Demand implies $x_0 = \frac{a-p_0}{b}$ and $x_1 = \frac{a-p_1}{b}$. Given observed values for the x_i and p_i for two consecutive periods, we can solve for the parameters to give the local approximation of utility, which implies $b = \frac{(p_0 - p_1)}{(x_1 - x_0)}$. Given b, $a = bx_i + p_i$.

Estimating the welfare change requires measures for prices and quality, which we construct from the CQPI. The change in CQPI gives a lower bound for the welfare change for the representative individual. If prices fall, consumers can afford the same average quality of washer at a lower price. Thus, assuming no change in behavior, consumers have ($-\Delta$CQPI) more income to spend on other goods and services. This extra income measures the *Slutsky compensation*, equal to the distance between A and D in Figure 2, which also equals the change in the CQPI. This change also implicitly measures the shift in the price of quality: $y_D - y_A = x_0(p_0 - p_1) = \Delta\text{CQPI}$. Without loss of generality, fix $p_0 = 1$, which implies

$$p_1 = 1 - \frac{\Delta\text{CQPI}}{x_0} \tag{6}$$

The last needed piece is a measure of quality. Since we set the initial price of average quality to 1, x_0 is simply defined as average retail price of washers in the initial period, which we denote $\bar{w}_0$. As washer prices decline, consumers substitute toward higher quality, so the change in average retail price relative to the change in CQPI reflects substitution toward quality. One can scale this change in different ways, but it mainly affects the measures of a and b. We measure $x_1 = \frac{\bar{w}_1 - \text{CQPI}_1}{p_1}$. Thus, the change in the value of quality, $p_i x_i$, equals the change in average price minus the change in constant-quality price.

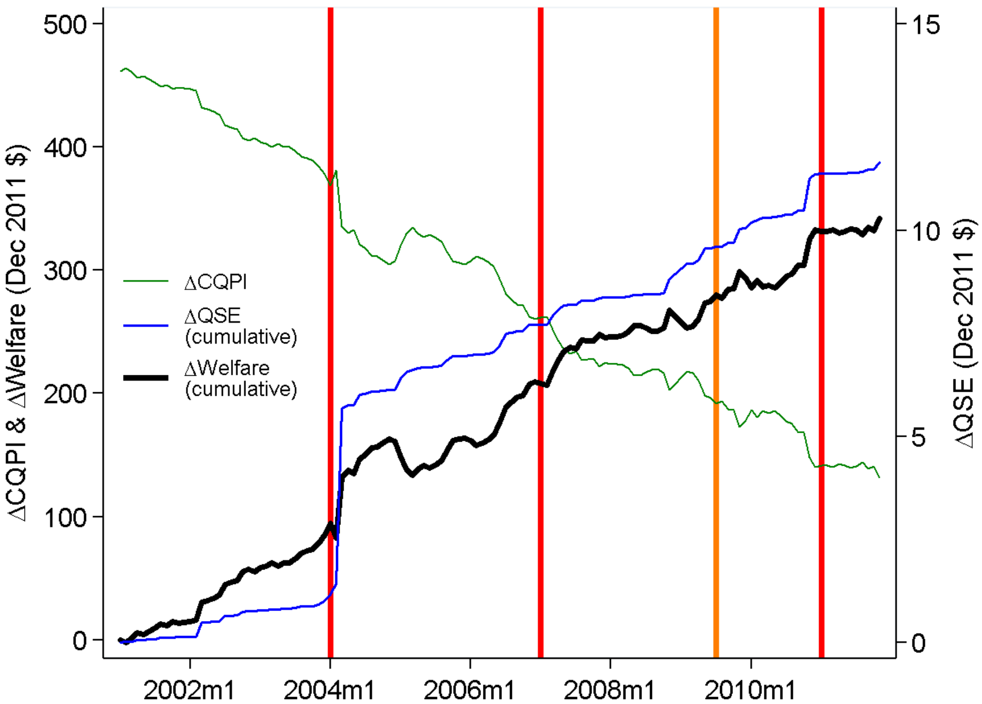
Note that if there were no substitution toward quality then the Slutsky compensation—equal to ΔCQPI—would equal the welfare change. We therefore call the difference between ΔW and ΔCQPI the Quality Substitution Effect (QSE).

Figure 3 summarizes the trend in the CQPI and the cumulative changes in consumer welfare and QSE between 2001 and 2011. The CQPI fell by \$330.36 over time, generating an estimated consumer welfare gain of \$342.00; the difference we attribute to the cumulative change in QSE, which denotes the additional utility from substituting to higher quality washers. A sharp drop in the CQPI occurred around the 2004 policy change, which also corresponds to the biggest jump in consumer welfare gain and QSE. There also appears to be accelerated welfare gains shortly after the 2007 policy change and a bit before the 2011 policy change, although these are less discernible.

Note that because the policy changes were anticipated far in advance of implementation, and affect the manufacture of washers but not their sale, there is no reason to expect a sharp discontinuity at the time of policy change. As a result, it is reasonable to model changes in quality and prices as a reflection of consumer choice. That is, policy changes may have affected costs of production by forcing production of more efficient units, or by encouraging pre-manufacture and storage of banned less-efficient products. These cost changes would presumably be reflected to some degree in prices, depending on market structure. It therefore may seem surprising that prices actually fell more rapidly around the times of the standard changes while quality rose.

Although policy changes appear to benefit consumers, there are important caveats. First,

Figure 3: Change in Constructed CQPI, QSE, and Consumer Welfare



Note: The figure illustrates the cumulative change in consumer welfare and quality substitution effect (ΔQSE), and the trend in the constructed CQPI between 2001 and 2011. The red solid vertical lines pertain to the simultaneous ME and ES policy changes in January of 2004, 2007 and 2011; while the orange solid vertical line pertains to the ES policy change in July 2009.

Source: The NPD Group; authors' calculation.

the welfare analysis is based on a representative consumer model. In reality, however, different consumers care to different degress about various product characteristics, an aspect of demand that the model may not fully capture. Second, while we might attribute at least some of the consumer welfare gains to standard changes, through intensified price competition and fall in prices adjusted for quality change (Ronnen, 1991), it's not clear how much of the overall decline in prices and improvement in quality would have occured in the absence of the standard changes. Empirically overcoming these caveats would require a model or research design that could account for and accurately measure consumer and product heterogenity.

Discrete choice models like Berry et al. (1995) (BLP)and McFadden and Train (2000) can account for heterogeneity of preferences; however, most discrete choice models impose restrictive and otherwise questionable assumptions in order to extract precise distributions of consumer utilities (Berry et al., 2004). Consequently, measurement of consumer welfare gains resulting from introduction of new products remains an issue. Different estimates exist, which are largely due to use of different methods and data on consumer characteristics that rarely exist (Petrin, 2002; Berry and Pakes, 2007). Our method offers a simple and transparent way of calculating consumer welfare price changes and does not require additional data that relates characteristics of consumers to characteristics of the products they purchase.

6 Effects of Policy Changes

In this section we examine the effect of imposing more stringent standards on CQPI, quality index and welfare estimates. We estimate these effects using differences (pre/post) and difference-in-differences. For difference in differences, we use refrigerators as a control, since there were no minimum standard changes for refrigerators over the time frame. Refrigerators are an imperfect counterfactual, however, as there may be spillover effects from the standard change. For example, due to marketing or technological spillovers, the 2004 minimum energy standard might incite some manufacturers to simultaneously schedule introduction of new models for multiple appliances.

Figure 4 plots trends in the CQPI, quality index and the cumulative change in welfare for washers and refrigerators over the study period. Table 3 summarizes the average change in the CQPI, quality index and welfare estimates for washers and refrigerators around the 2004, 2007 and 2011 simultaneous minimum efficiency (ME) and Energy Star (ES) policy changes, as wells as the 2009 ES policy change.

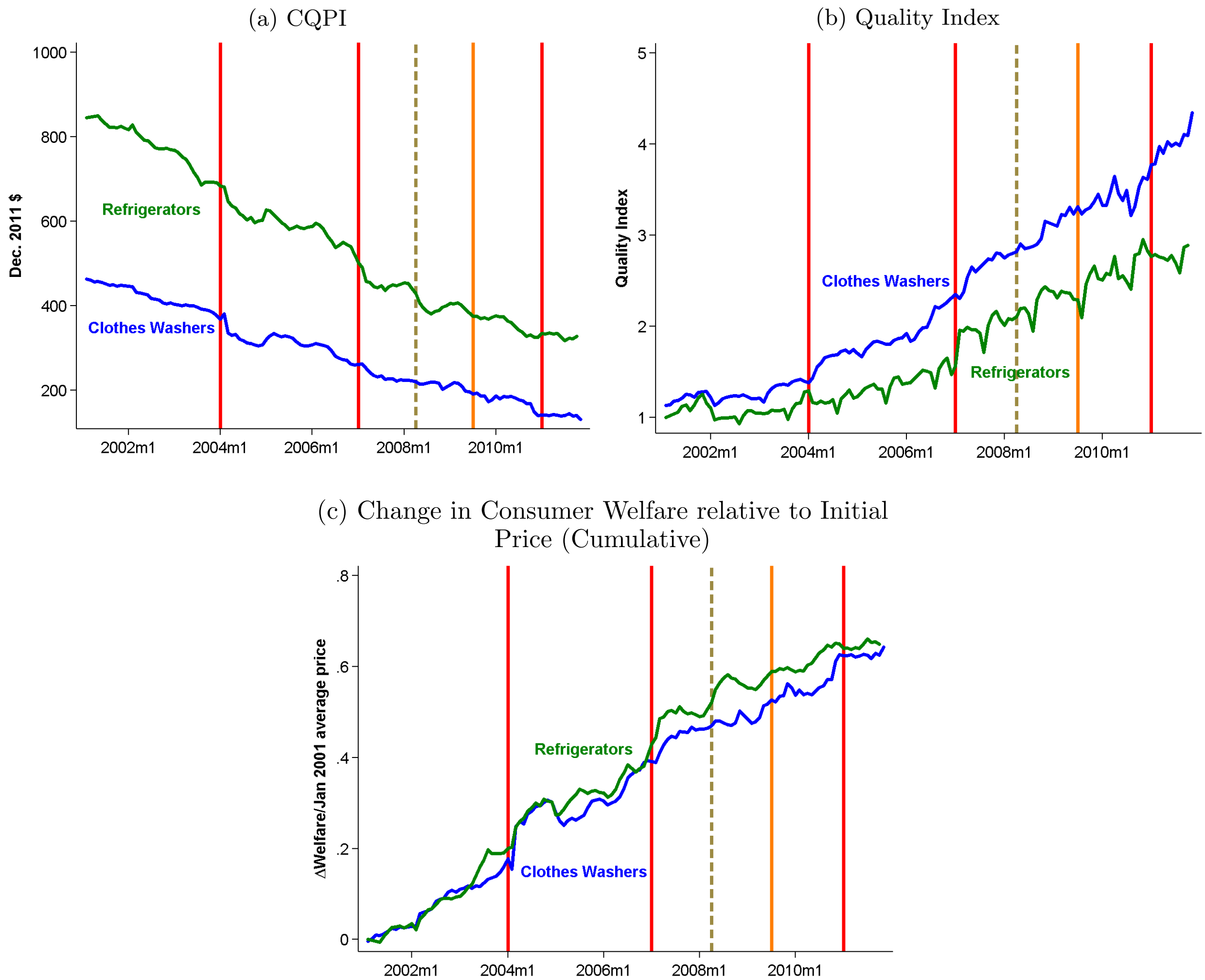
Table 3: Average Change in CQPI, Quality Index and Welfare, Washers vs. Refrigerators, 2001-2011.

Period	Clothes Washers			Refrigerators		
	CQPI	Quality	Welfare	CQPI	Quality	Welfare
Pre-2004	-2.147	0.011	2.173	-6.147	0.006	6.390
2004 ME & ES Policy	**-6.631**	**0.024**	**7.064**	**-8.164**	**0.007**	**8.474**
Post-2004 Policy	-0.662	0.016	-0.606	-2.267	0.012	2.427
Pre-2007 Policy	-3.006	0.012	3.050	-3.173	0.017	3.281
2007 ME & ES Policy	**-5.050**	**0.051**	**5.131**	**-9.129**	**0.038**	**9.487**
Post-2007 Policy	-1.444	0.021	1.465	-4.043	0.020	4.215
2009 ES Policy	**-2.348**	**0.028**	**2.461**	**-1.839**	**0.027**	**2.318**
2011 ME & ES Policy	**-3.545**	**0.050**	**3.362**	**-3.867**	**0.021**	**2.135**

Note: The table summarizes the average change in the constructed constant quality price index (CQPI), quality index and consumer welfare (measured as ΔConsumer Surplus) for clothes washers and refrigerators between 2001 and 2011. Except for the 2009 ES Policy that runs between January-December 2009, each period pertains to a 6-month window before and after the date of the policy change. For example, the 2004 policy change refers to the period July 2003-June 2004.

Sources: The NPD Group, authors' calculations.

Figure 4: CQPI, Quality Index and (Cumulative) Welfare Change, Washer vs. Refrigerator, 2001-2011



Note: The figure presents trends in the constructed constant quality price index (CQPI), quality index and the cumulative change in welfare relative to January 2001 sales-weighted average price for clothes washers (blue line) and refrigerators (green line) between 2001 and 2011. The red solid vertical lines pertain to the simultaneous ME and ES policy changes for clothes washers in January of 2004, 2007 and 2011; while the orange solid vertical line pertains to the ES policy change in July 2009. The brown dashed vertical line represents the ES policy change for refrigerators in April 2008. Prices are in December 2011 dollars.

Source: The NPD Group; authors' calculation.

Because policy changes were announced well in advance of implementation, and may affect product introduction and pricing well before and after the change, we define a policy change window that includes 6 months before and after the policy change. For example, for the January 2004 policy change we assign all months from July 2003 up to June 2004 to the policy treatment. In an appendix we report results when the window includes only three months (see Appendix D). To the extent feasible, we compare the changes within the policy period to those in one year prior and one year after the policy period. For example, the 2004 policy change refers to the period July 2003-June 2004, and we compare changes during this period with those in July 2002-June 2003 and July 2004-June 2005.

The results show that average changes in CQPI, quality index and welfare estimates are larger around policy changes relative to previous and succeeding periods. For example, the average monthly drop in the CQPI for clothes washers around the 2004 ME and ES policy change was about \$4.50 and \$6.00 more than the pre- and post-policy periods, respectively. Interestingly, average decline is also larger for refrigerators during the 2004 and 2007 policy changes.

Statistics for the two appliances follow similar trends and fluctuations, including the significant drop around 2004 policy change. Based on the data alone, it is hard to know whether the correlated effects are due to unobserved factors, like the boom in housing, or because the policy change for washing machines also affected refrigerators. Although the sharp effects right at the policy changes in 2004 and 2007 leans against the idea of a common unobserved factor.

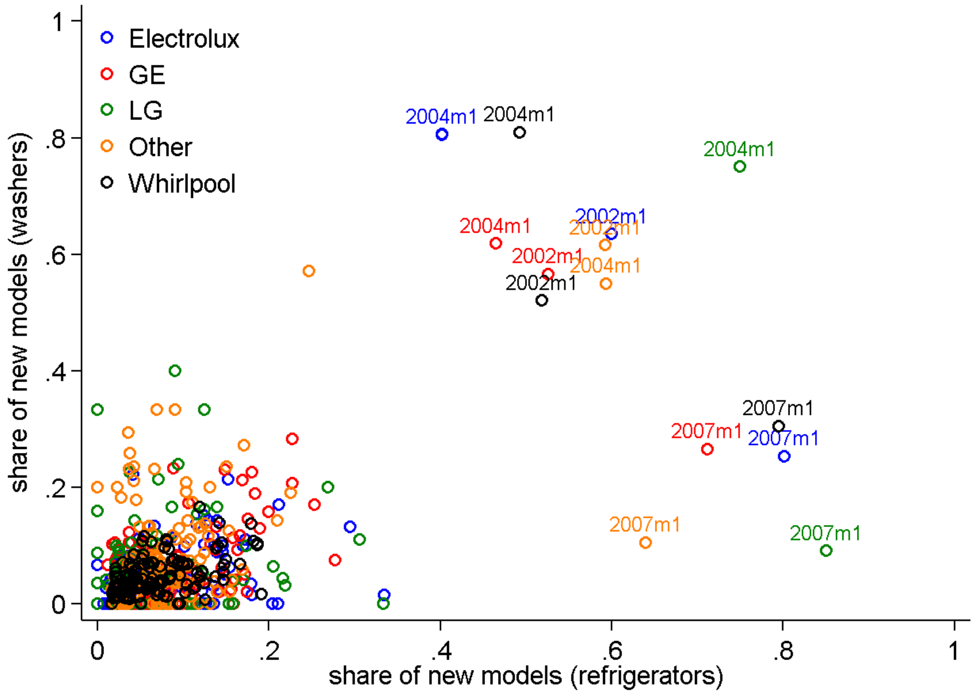
To obtain some sense of whether spillover effects seem likely, we consider whether the timing of product introductions for clothes washers are correlated with those of refrigerators. At the manufacturer level, we find significant correlation in the share of new models between clothes washers and refrigerators, particularly around the policy changes in 2004 and 2007 (Figure 5). We performed the same exercise at the brand level and find the same significant correlation, particularly for major brands of washers and refrigerators (see Appendix E).

Despite its potential limitations, we employ a standard difference-in-differences (DID) approach to estimate a lower bound of the effect of the standard change, using refrigerators as the control. We view these estimated effects as a lower bound due to large apparent effects from looking at differences, and potential spillover effects that we saw in Figure 5. The dependent variable, y_t, is the percentage change in CQPI or quality index, or level change in welfare; *Policy* is a dummy variable that turns on at the time the new standard is assumed to have effected the outcome variables; *Treatment* is a dummy variable equal to one for clothes washers and zero for refrigerators; and ε_t is the usual error term (equation 7). The coefficient of interest is β_3, which accounts for policy-affected periods of the treatment.

$$y_t = \beta_0 + \beta_1 Policy + \beta_2 Treatment + \beta_3 (Policy \cdot Treat) + \varepsilon_t \tag{7}$$

Regression results are reported in Table 4. Columns labeled (1) pertain to the standard DID; (2) include year-month fixed effect to control for potential idiosyncratic shocks in each time period; and (3) include the intersection of month and refrigerator dummies to control for seasonality that

Figure 5: Correlation in the share of new models between washers and dryers, 2001-2011.



Note: The figure shows the correlation in the share of new models at a particular time period between washers and refrigerators. A list of manufacturers and their subsidiary brands are presented in Table 8.

Source: The NPD Group; authors' calculation.

we observed for refrigerators. Results are fairly intuitive. Quality-adjusted unit price drops while overall quality and consumer welfare improve on the average as a result of the policy change. The estimates appear to be small and statistically insignificant. Notwithstanding, these estimates are the lower bound of the potential effect of standard change, which means that, at worst, the overall welfare impact of the standard change was negligible.

7 Quality Trend of Clothes Washers Over Time

Given a measure of constant-quality price, and assuming quality is increasing in price within any given month, we construct a measure of quality using the difference between observed average market price and the CQPI. We measure this difference by the ratio between average price and CQPI, excluding entering and exiting models and adjusting for vintage effects as described above for the CQPI. Because average price is relatively flat, and CQPI declines sharply, the quality index must be increasing, as shown in Figure 6. Interestingly, the index increases more quickly around the times of policy changes. Note that acceleration in quality increases around policy changes is

Table 4: Results from Estimating the Average Effect of the Policy Change.

	Dependent Variable								
Variables	**%Δ CQPI**			**%Δ Quality**			**Δ Welfare**		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Treatment	0.070	0.165	0.192	0.042	-0.246	4.434*	-1.884*	-2.088*	-1.332
	(0.263)	(0.213)	(0.736)	(0.753)	(0.662)	(2.256)	(1.019)	(0.846)	(2.509)
Policy Dummy	-0.498	-1.948**	-0.745	0.324	-13.326***	-15.750***	2.176	5.957**	5.781*
	(0.305)	(0.941)	(1.167)	(1.241)	(2.031)	(3.377)	(1.627)	(2.915)	(3.271)
Treatment x Policy	**-0.774**	**-0.818***	**-0.804***	**0.311**	**0.565**	**0.441**	**0.898**	**0.869**	**0.858**
	(0.600)	**(0.485)**	**(0.425)**	**(1.355)**	**(1.372)**	**(1.026)**	**(2.157)**	**(1.549)**	**(1.420)**
Constant	-0.547***	0.298	-1.268	0.922***	13.568***	16.296***	3.428***	-0.044	2.256
	(0.167)	(0.213)	(1.000)	(0.677)	(0.662)	(3.113)	(0.888)	0.846	(3.008)
Year-month fixed effect	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Month x ref dummy	No	No	Yes	No	No	Yes	No	No	Yes
R-squared	0.052	0.707	0.785	0.003	0.560	0.800	0.039	0.744	0.817
Adj. R-squared	0.040	0.393	0.510	-0.009	0.088	0.544	0.027	0.469	0.583
Observations	254	254	254	254	254	254	254	254	254

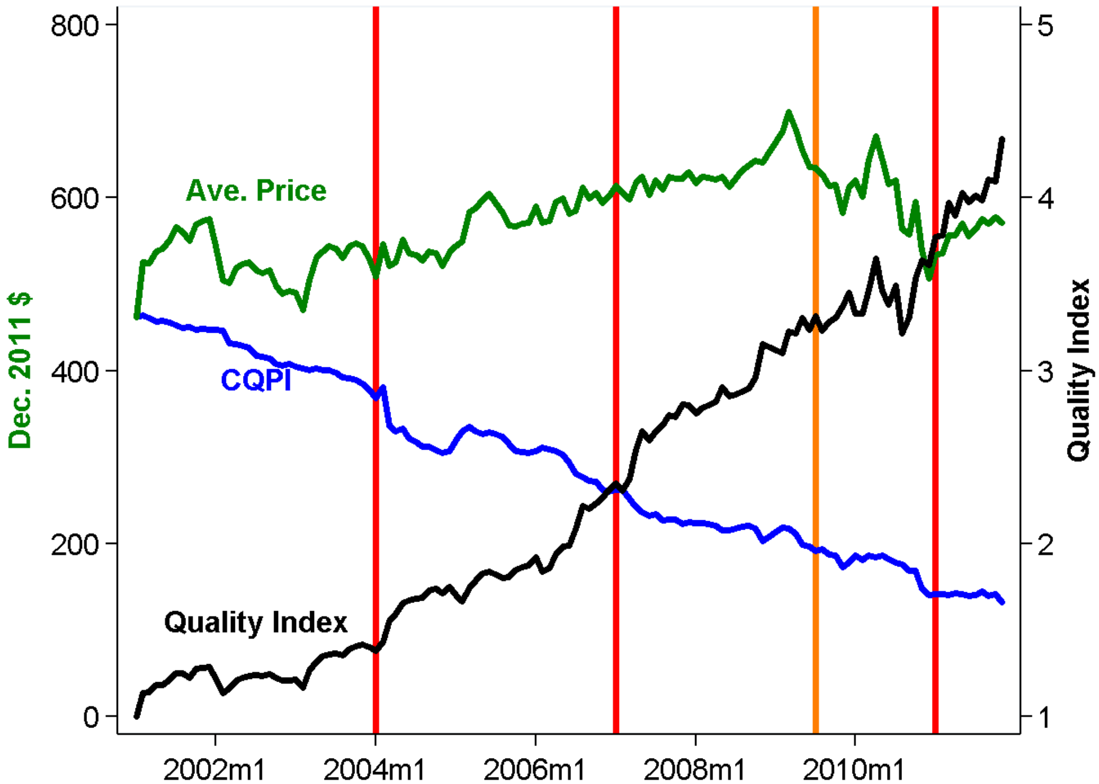
Note: The table presents the results from estimating equation 7, which estimates the average effect of the policy change on CQPI, the Quality Index and estimated welfare. Treatment is a dummy variable equal to one if the observation is for the appliance that is affected by the standard (i.e. clothes washer); Policy is a dummy variable that turns on at the time new standard is perceived to have effect on the key variables. We assume that the effect of the policy takes place within a 6-month period. For example, the 2004 policy change, due to its anticipatory nature, is perceived to have effect starting July 2003 up to June 2004. Columns labeled (1) pertain to the standard difference-in-difference (DID) approach; (2) include year-month fixed effect to control for potential idiosyncratic shocks in each time period; and (3) include the intersection of month and refrigerator dummies to control for the fairly robust seasonality that we observed for refrigerators. Robust standard errors are in parentheses. *, **, *** represent statistical significance at 10,5, and 1 percent, respectively.

Sources of Data: The NPD Group, authors' calculations.

not due to vintage effects (e.g., a large introduction of new models), as these have been excluded. Instead, it comes from substitution toward higher-quality continuing models as prices generally fall.

To validate price-based estimates of overall quality, it helps to identify whether particular attributes, like energy efficiency, are associated with it. Two observable characteristics directly contribute to measures energy efficiency metrics for clothes washers: spin speed (measured by the number of revolutions per minute or RPMS) and capacity (measured in cubic feet). Clothes washers with higher spin speeds extract more water from clothes, which reduces time and energy spent on drying. Models with higher capacity thereby reduce the number of loads for laundry for a typical household. Over time, we can see that more clothes washers have higher spin speed and capacity (Figure 7). More importantly, we see market's inclination towards washers with higher spin speed and capacity right around the imposition of more stringent ME and ES standards. For example, the shares of clothes washers that have spin speed of 649 rpms and lower fell around January 2004 and 2007. Meanwhile, clothes washers that have 1000-1299 and 1300-1599 rpms significantly increased around 2004 and 2007 policy changes, respectively. Conversely, the share of lower-capacity clothes washers fell more rapidly around the policy changes, while those that have higher capacity (i.e. 3.5-3.9 and more than 4.5 cu. ft.) grew around January 2004 and 2007.

Figure 6: Trend in Average Price, CQPI and Quality Index, Jan. 2001-Dec.2011



Note: The figure shows that trend in the average price-CQPI ratio. Masked models and the models introduced at a particular time period were dropped in calculating the ratio. Both average price and CQPI are net of vintage-fixed effect to control for any potential effect of introducing new models at a specific time period. The red solid vertical lines pertain to the simultaneous ME and ES policy changes in January of 2004, 2007 and 2011; while the orange solid vertical line pertains to the ES policy change in July 2009.

Source: The NPD Group; authors' calculation.

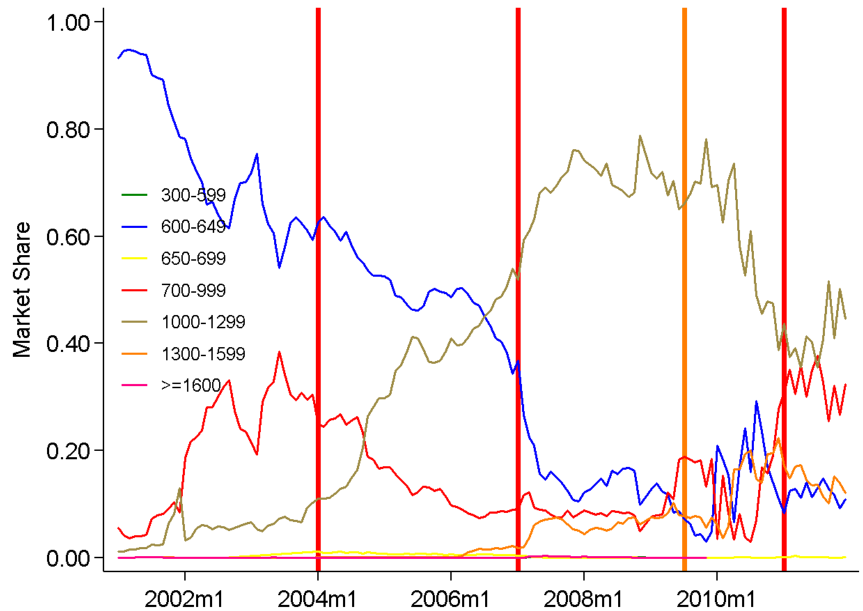
While energy efficiency improves over time, we also observe improvements in the quality of each model that do not necessarily contribute to the energy efficiency metric for clothes washers. Figures 8 to 9 illustrate the trend of market share of characteristics that affect the cleanliness of clothes (number of wash cycles options); convenience (i.e. whether controls are mechanical or electronic); and space requirement (i.e. whether the model is regular or portable and within each category, if the model is side-by-side, stackable, pre-stacked, or combined washer/dryer). Panels (a) & (b) in Figure 8 illustrate how sales shifted toward more space-saving front-loading and portable models starting with the policy change in 2004. There were also shifts towards stackable models starting in 2004, both in regular and portable types of clothes washers.

Over time, more models also have more wash cycle options with electronic controls (Figure 9). Particularly around 2004, washers that have 11-15 wash cycle options increased significantly, taking more than 20% of the share of the dominant low-wash-cycles models. The share of models with a larger number of wash cycles continues to rise and becomes dominant around the 2011 policy change. The share of models with more than 16 wash cycle options also increased significantly around the 2009 Energy-Star threshold update.

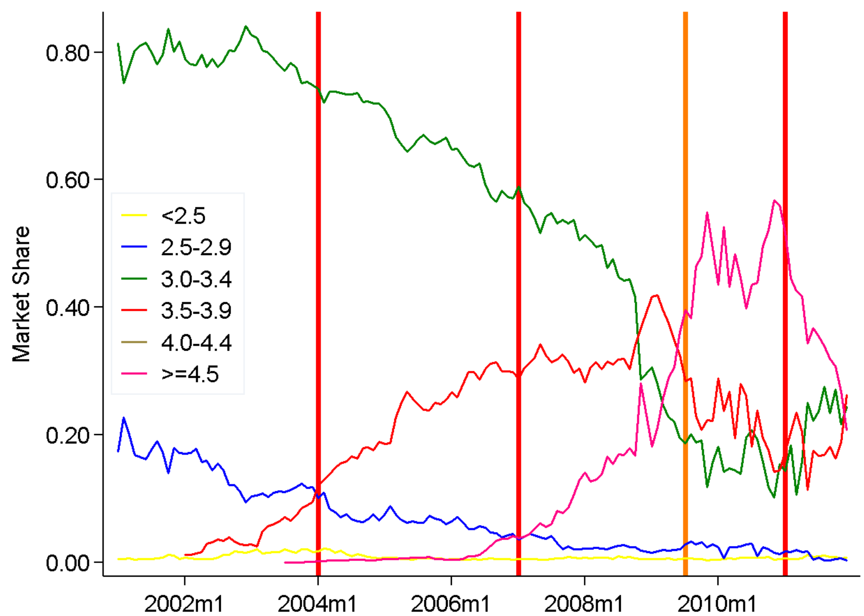
The 2011 policy change had minimal or counter-intuitive effect on most characteristics for which we have data. Newer features appeared during this period about which we do not have data. These include steam wash technology and direct drive technology that is reportedly quieter than traditional belt and pulley mechanisms.

Figure 7: Market share by product category, energy-efficiency characteristics, Jan. 2001-Dec. 2011

(a) Revolutions per minute



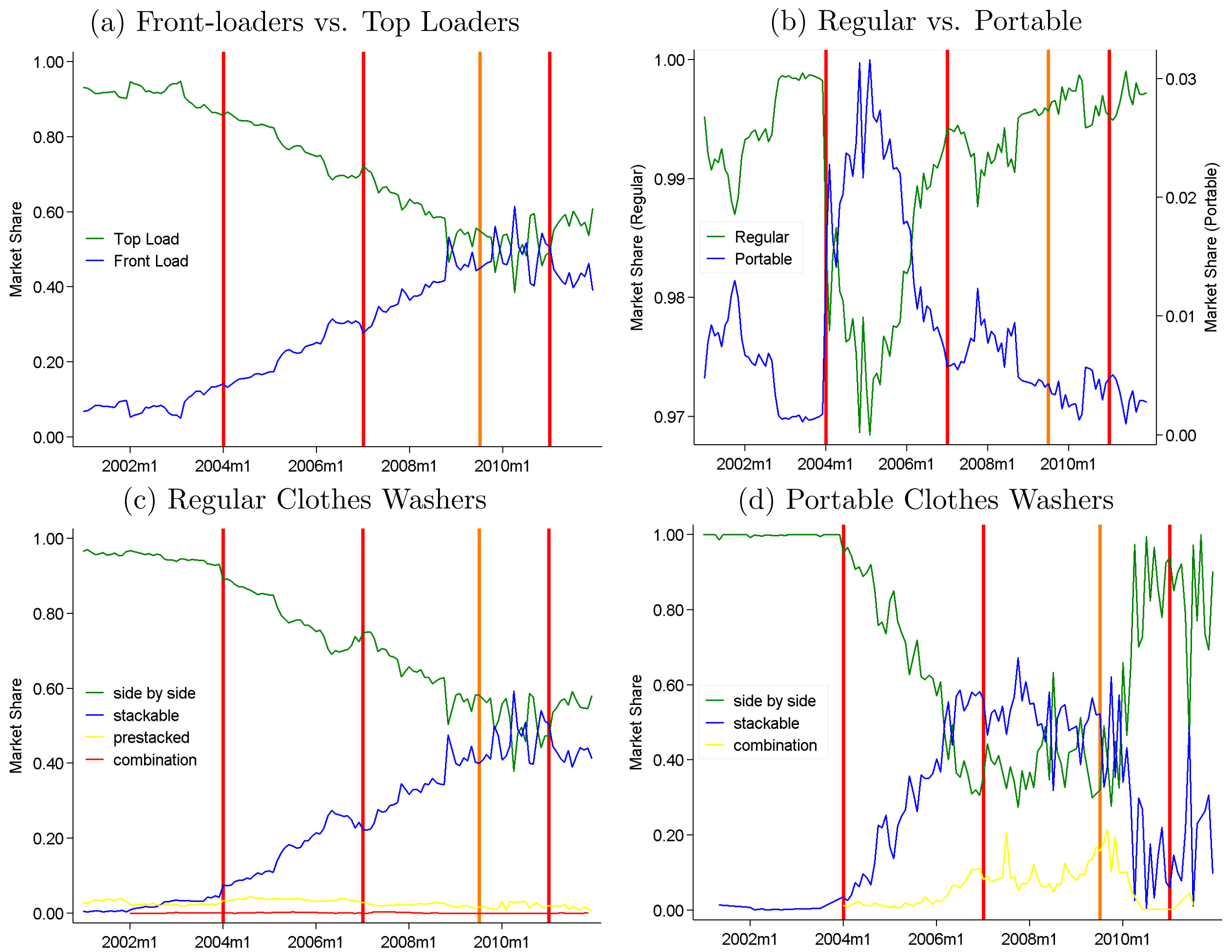
(b) Volume/Capacity



Note: The figure shows market shares of the product characteristics between 2001 and 2011. Listed product characteristics include the number of wash cycles, revolutions per minute (RPMS) and capacity/volume (in cubic feet). The red vertical solid lines mark simultaneous minimum efficiency and Energy Star policy changes in January of 2004, 2007 and 2011; the orange vertical solid line marks the Energy Star policy change in July 2009.

Source: The NPD Group; authors' calculation.

Figure 8: Market share by product category, space-saving characteristics, Jan. 2001-Dec. 2011

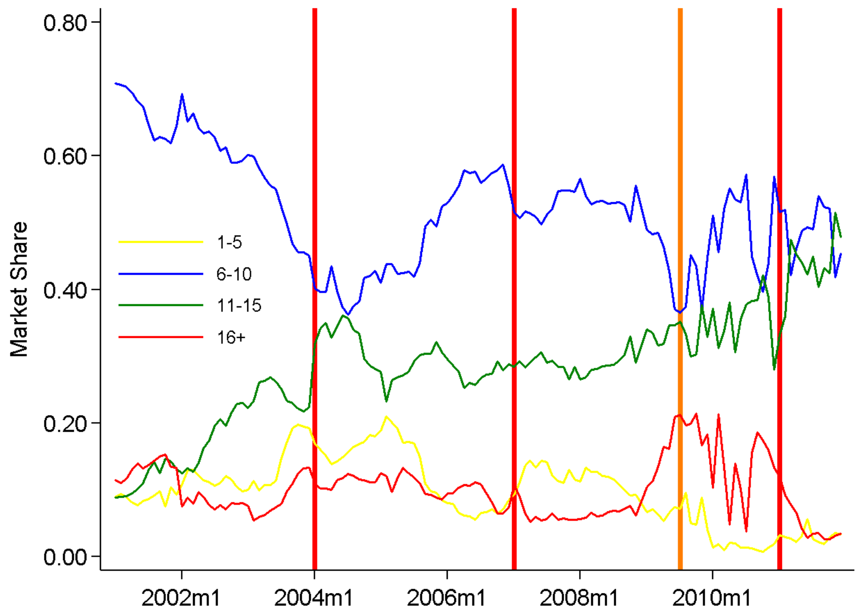


Note: The figure shows that trend in the market shares of categories in each of the product characteristics between 2001 and 2011. Listed product characteristics include whether the washer if front-loading or top-loading (panel a), regular or portable (panel b), and the type of clothe washers in the regular (panel c) and portable (panel b) categories. The red vertical solid lines pertain to the simultaneous ME and ES policy changes in January of 2004, 2007 and 2011; while the orange vertical solid line pertains to the ES policy change in July 2009.

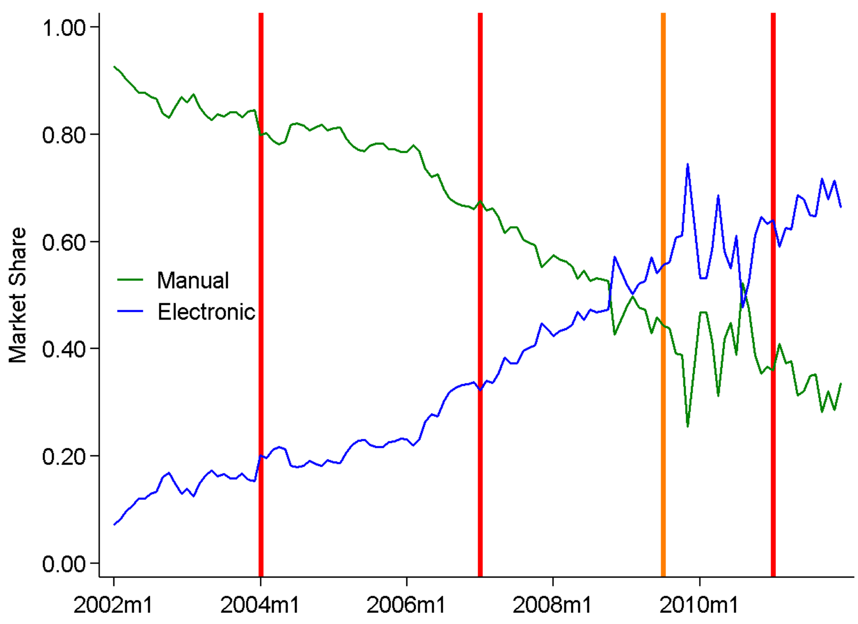
Source: The NPD Group; authors' calculation.

Figure 9: Market share by no. of wash cycle options and panel control type, Jan. 2001-Dec. 2011

(a) No. of wash cycles options



(b) Type of controls



Note: The figure shows that trend in the market shares of categories in each of the product characteristics between 2001 and 2011. Listed product characteristics include the number of wash cycle options, and the type of controls in the panel. The red vertical solid lines pertain to the simultaneous ME and ES policy changes in January of 2004, 2007 and 2011; while the orange vertical solid line pertain to the ES policy change in July 2009.

Source: The NPD Group; authors' calculation.

8 Entry, Exit and Average Vintage

Above we showed evidence that prices decline with vintage, and briefly suggested that policy-driven entry and exit of models may be affecting average vintage and the price of washers. One hypothesis is that the vintage effect derives from competition, that entry of new models pushes manufactures to lower prices of older vintages. Thus, a natural measure for competition is average vintage. For any given model, regardless of vintage, the lower is average vintage, the more new, presumably higher-quality models with which to compete. By forcing gradual exit and entry, standards may significantly alter the distribution of vintages and thereby affect innovation and competition. To test this hypothesis, we calculated average vintage, or average time since market introduction, and found that average vintage declines sharply around the times of major policy changes (Figure 10).

A concern with interpreting the data in Figure 10 is that drops in average vintage may not be solely due to the regulatory changes. For example, average vintage drops during early months of 2002, 2006 and 2008, when no policy changes occurred. These changes may be a result of a large firm's strategy to introduce models ahead of the others to take some revenue shares from existing yet eventually obsolete products. Nevertheless, the particularly sharp declines in 2004 and 2007 suggest energy efficiency standard changes had an important role in product entry and exit.

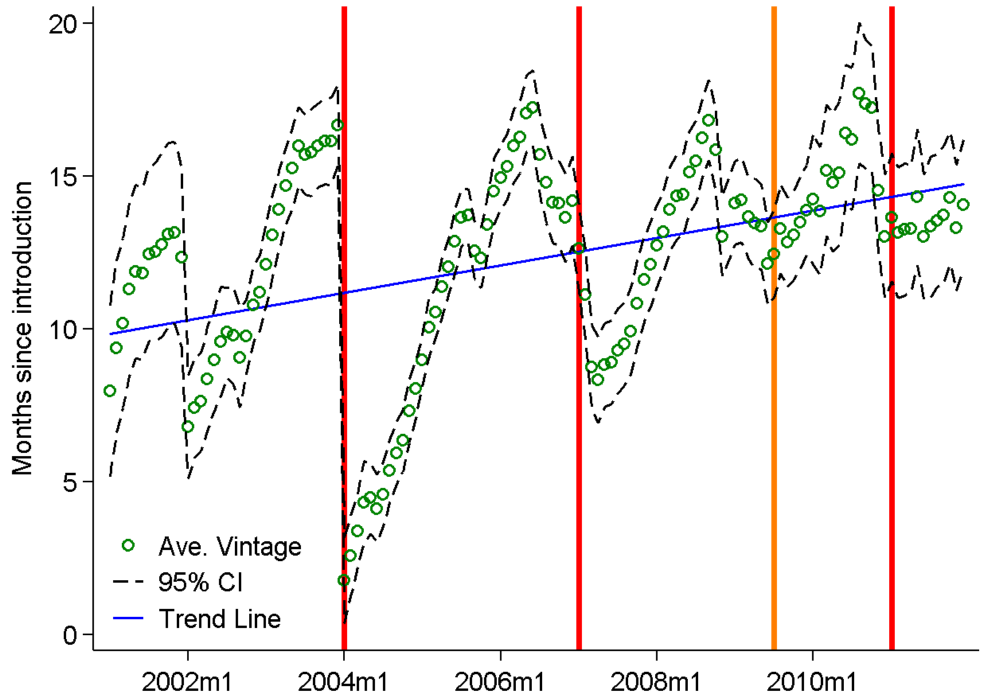
To examine the relationship between product entry and exit on price, we estimate the following reduced-form regression model:

$$p_{it} = \alpha_i + \beta_0 \, \overline{vintage}_{-i,t} + f(vintage_{it}) + g(vintage_{it}) \, \overline{vintage}_{-i,t} + month_k + \varepsilon_{it} \tag{8}$$

where p_{it} denotes the price of model i at time t, $\overline{vintage}_{-i,t}$ is the average vintage (weighted by current sales) of all models excluding i at time t, and $f(vintage)$ and $g(vintage)$ are restricted cubic splines of model-specific vintage, representing periods since first introduction. The second spline is interacted with average vintage to account for the possibility that prices of different vintages are more or less affected by average vintage. The spline functions allow price to change smoothly and flexibly over the life span of the product. The variable *month* denotes month dummies to account for possible seasonality in the price trend and α_i denotes the model fixed effect to account for unobserved time-invariant heterogeneity, like size and other model specifications, as well as unobserved quality attributes. ε_{it} is the usual error term.

In this model we cannot use time period fixed effects as we do in equation 2, because while average vintage is slightly different for different models, they are highly correlated given each model excluded is a small share of the whole market. Thus, average vintage is very nearly linearly dependent with time period fixed effects. Within models, a linear time trend is also perfectly collinear with model-specific vintage, so an overall trend is not identified either.

Figure 10: Average Vintage of Clothes Washers, 2001-2011.

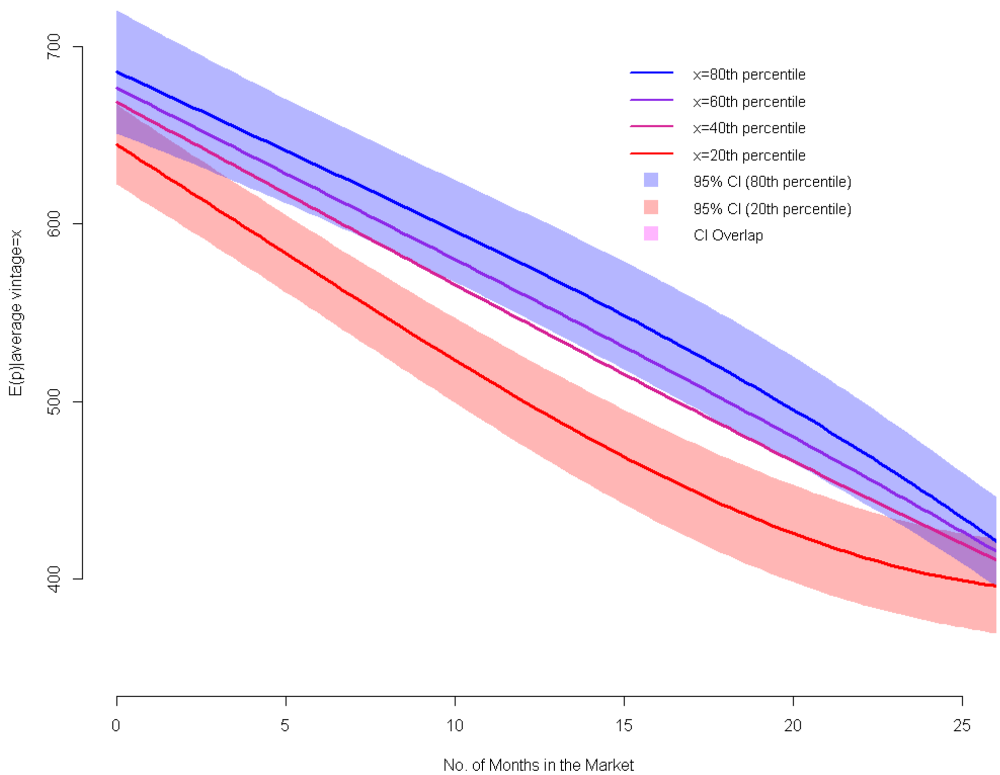


Note: The figure shows the trend in average vintage of clothes washer between 2001 and 2011. Each point represent the sales-weighted average vintage at a particular time period. The solid red vertical line represents the effective date of simultaneous policy changes in the federal minimum energy efficiency standard and Energy Star certification threshold, while the orange vertical line is for the Energy Star threshold update that took effect in July 2009. Observations with prices falling below $100 and log sales below 1 were dropped as these observations are outliers and appear to be unrealistic.

We use the estimates from equation 8 to predict the price trend of a typical clothes washer holding average vintage constant at different quantiles. Figure 11 plots this predicted price across the first two years of a clothes washer in the market, holding average vintage equivalent to about 10 months (20th percentile), 13 months (40th percentile), 14 months (60th percentile), and 15 months (80th percentile). The difference between the trend line at 10 months and at 15 months is statistically significant. Figure 11 shows how average vintage of clothes washers relates to the level and slope of the predicted price trend of a representative clothes washer. All else the same, increasing average vintage from 10 to 15 months is associated with a 10% price increase.

If the firm's pricing policy with respect to vintage were solely due to decreasing production cost over time, the introduction of new products in the market, which lowers average vintage but not own-model vintage, should not influence the firm's pricing policy. The data thus provide evidence of imperfect competition. Taking average vintage into account also causes the relationship between price and own-model vintage to become more strongly negative. This pattern makes sense: because own-product vintage tends to be associated with average vintage, and these two factors have opposite effects in a monopolistically competitive market, the effects confound each other if not estimated jointly. Significance tests are summarized in Table 5.

Figure 11: Life-Cycle Pricing of Clothes Washers Under Different Average Vintage



Notes: The figure shows the trend in the predicted price of a representative clothes washer using equation 8 during its first two years. We estimate equation 8 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given an average vintage of clothes washer. The 20th, 40th, 60th and 80th percentile correspond to 9.58, 12.63, 13.64, 14.80, respectively. The distribution of average vintage is weighted by current sales.

9 Within and Between Brand Competition

In this section, we look more closely at entry and exit dynamics of models within and between firms. Specifically, we examine how firms adjust prices of their own continuing models when the firms themselves introduce new models, as well as how they adjust prices when competing firms introduce new models. In other words, we attempt to disentangle the influence of average vintage into cannibalization and external competition.

A literature on cannibalization and innovation offers mixed propositions (Nijssen et al., 2005). On the one hand, some argue that firms with some degree of market power are more likely to be

Table 5: Analysis of Variance for price (real)

Variables	d.f.	F-statistic	p-value
Average Vintage	1	41.77	<0.000
Spline Functions	4	40.73	<0.000
Interaction Terms	4	10.09	<0.000
All Variables	20	54.57	<0.000
R-sq. (within)			0.293

Notes: The table reports the F-tests for the joint significance of key explanatory variables and their interactions with the age (in terms of number of months) of the clothes washer in the market. Our model uses restricted cubic splines with 5 knots, which results in four factors in the regression equation. The key variables include the average vintage (1 degree of freedom [d.f.]) and the interactions with the four vintage factors (4 d.f.). We used STATA command *mkspline2* in estimating the spline functions.

Source of data: The NPD Group.

the drivers of technological improvement. This is based on the idea that established firms use their market power to preempt potential entrants (Gilbert and Newbery, 1982). On the other hand, some suggest that innovation comes from younger firms, since established firms may fear cannibalizing their earlier investments (Reinganum, 1983).

To assess how a firm's product pricing is affected by its own and other firms' introduction (or withdrawal) of products, we break average vintage into two components, own-firm average vintage and other-firm average vintage. Specifically, denote $\overline{vintage}_{-i,c,t}$ as the average vintage (weighted by current sales) of other products within the same firm at time t but excluding the current model i and $\overline{vintage}_{-c,t}$ as the average vintage (weighted by current sales) of models manufactured by other firms at time t. Like the model in the last section, we consider interactions between own-model vintage and average vintage measures.

$$\begin{aligned} p_{i,c,t} \quad = \quad & \alpha_i + \beta_1 \, \overline{vintage}_{-i,c,t} + \beta_2 \, \overline{vintage}_{-c,t} + f_c(vintage_{i,t}) + \\ & + f_c(vintage_{i,t}) \, \overline{vintage}_{-i,c,t} + f_c(vintage_{i,t}) \, \overline{vintage}_{-c,t} + month_k + \varepsilon_{it} \end{aligned} \tag{9}$$

We use the estimates from equation 9 to predict the price trend of a typical clothes washer holding average vintage of models within brands constant. Panel (a) in Figure 12 plots this predicted price across the first two years of a clothes washer in the market, holding within-brand average vintage equivalent to about 8 months (20th percentile), 11 months (40th percentile), 13 months (60th percentile) and 17 months (80th percentile). We do this prediction assuming between-brand average vintage is equivalent to about 10 months (20th percentile).[3]. We find no statistically significant difference between trend lines in different months. Panel (b) plots the predicted price trend of a typical clothes washer holding average vintage between brands constant at 20th, 40th, 60th and 80th percentile. The difference between the trend line at 10 months and at 15 months is statistically significant (Figure 17). If we abstract from the non-linear effect of the within- and between-brand average vintage, reducing the average vintage from 15 months to 10 months is associated with a 3% price decrease, all else the same (Table 6).

Table 6: Results from regressing real price of a washer model at a particular time period

	(1)	(2)
β_1, average vintage *within brand*	2.017***	
	(0.379)	
β_2, average vintage *between brands*	3.145***	
	(0.630)	
β_1, average vintage *within manufacturer*		3.905***
		(0.427)
β_2, average vintage *between manufacturers*		0.744
		(0.462)
Constant	719.932***	722.204***
	(6.322)	(6.005)
Own Vintage Spline	yes	yes
Month-Fixed Effect	yes	yes
Model-Fixed Effect	yes	yes
Adj. R-Squared (within group)	0.298	0.300
Observations	38,282	38,477

Notes: The table reports the results from estimating equation 9 without the interaction effects. Columns (1) estimates the effects of within- and between-brands average vintage, and (2) estimates the effects of within- and between-manufacturer average vintage on price. Clustered standard errors are in parentheses. We use restricted cubic splines with 5 knots in estimating the spline function of vintage.

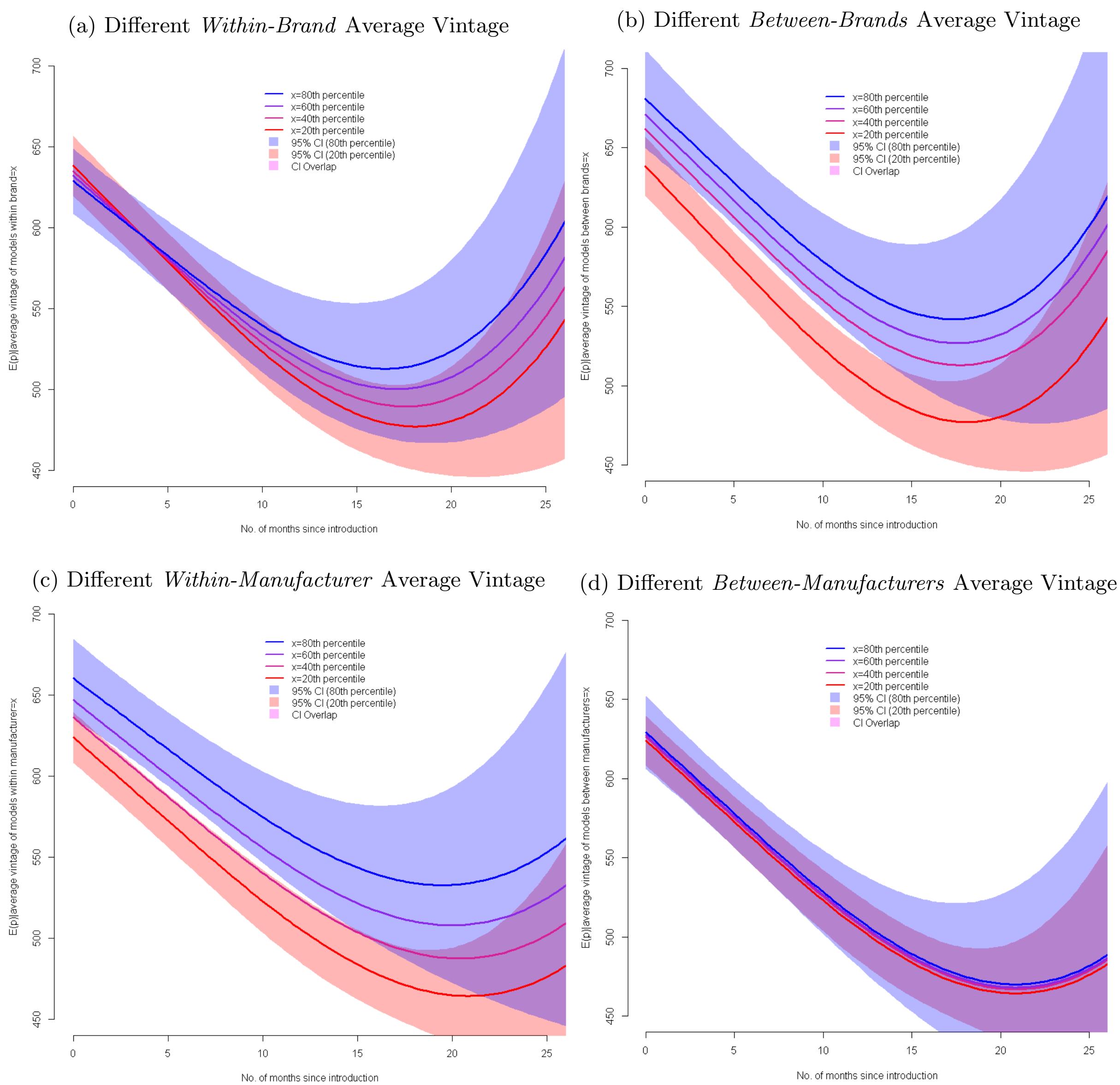
Source of data: The NPD Group.

Since the clothes washer market is dominated by large integrated manufacturers with several subsidiary brands (e.g. Whirlpool, General Electric and Electrolux), we assess whether the same pattern holds at the manufacturer level. We predict the price trend of a typical washer at different average vintage of models within the same manufacturer and between manufacturers. Figure 18 shows the predicted price of a typical clothes washer, holding average vintage of models within the same manufacturer constant at about 9 months (20th percentile), 11 months (40th percentile), 13 months (60th percentile) and 16 months (80 percentile).[4] The difference between

[3] Appendix F plots that assume contains plots that hold between-brand average vintage at 13 months (40th percentile), 14 months (60th percentile) and 15 months (80 percentile)

[4] We repeat this prediction for different between-manufacturer average vintages in Appendix Appendix F

Figure 12: Life Cycle Pricing of Clothes Washers



(a) Different *Within-Brand* Average Vintage

(b) Different *Between-Brands* Average Vintage

(c) Different *Within-Manufacturer* Average Vintage

(d) Different *Between-Manufacturers* Average Vintage

Note: The figure shows that trend in the predicted price of a representative clothes washer using equation 9 during its first two years. We estimate equation 9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a within-brand average vintage of clothes washer. The 20th, 40th, 60th and 80th percentile of within-brand average vintage correspond to 7.71, 10.67. 13.32 and 16.58, respectively. For the between-brand average vintage, the 20th, 40th, 60th and 80th percentile correspond to 9.62, 12.54, 13.67, and 14.90, respectively.

Source: The NPD Group; authors' calculation.

the trend line at 9 months and 16 months is statistically significant. All else the same, the decline of within-manufacturer average vintage from 16 months to 9 months is associated with a 5% price decrease. We make the same prediction for different average vintage between manufacturers. We find no statistically significant difference between price trends at any given average vintage between manufacturers. These findings imply that most and perhaps all the price declines associated with average vintage are associated with increased entry and exit of models that occur within the same manufacturer.

A reasonable interpretation of these results is policy-induced creative destruction. The imposition of more stringent regulation forces all firms in the clothes washer market to introduce newer models at the expense of the older ones. The clothes washer marker is dominated by large integrated manufacturers (e.g Whirlpool, General Electric and Electrolux) producing several brands of clothes washers and a number of relatively small independent manufacturers (e.g. Samsung and Fisher & Paykel). Firms, forced to bring new products to market meeting new standards, may find it more profitable to bundle other innovations that complement energy efficiency. Due to brand loyalty, and perhaps a general narrowing of product heterogeneity, older vintages from the same manufacturer face greater competition, inciting them to lower prices of an existing product (Padmanabhan and Bass, 1993).

To see if cannibalism is unique to those appliances that had more stringent energy efficiency standards over the sample period, we use refrigerator, room AC and clothes dryer as counterfactuals. None of these appliances had adopted or implemented a simultaneous minimum energy efficiency standards and Energy Star certification change during the study period. We use the estimation strategy presented in equation 9 for these appliances. Table 7 presents the regression results using equation 8 for refrigerators, room ACs, clothes dryers.

Interestingly, we also observe the same pattern in the clothes dryer market. We see that price declines in the clothes dryer market are strongly associated with cannibalism both at the brand and manufacturer level 7. This pattern can be explained by the complementarity of the two durable goods as consumers often purchase washers and dryers simultaneously. Thus, changes in clothes washer standards may have influence on the rate of model entry and exit, and pricing in the clothes dryer market. We do not observe this strong pattern of inter-brand cannibalism in the markets for room AC and refrigerators (Table 7), although cannibalism tends to drive down unit price at the brand level for refrigerators. This can be explained by the seasonality of refrigerators unit sales. The bulk of sales and price discounts occur during the first and last quarter of the year when the refrigerator market has generally lower unit price but more new models.

Table 7: Regression Results: Dependent Variable - Unit Price, Select Appliances.

	Clothes Dryers		Room AC		Refrigerator	
	(1)	(2)	(3)	(4)	(5)	(6)
β_1, average vintage within brand	2.535***		0.158		4.264***	
	(0.262)		(0.130)		(0.411)	
β_2, average vintage between brands	3.580***		0.999***		4.429***	
	(0.501)		(0.202)		(0.739)	
β_1, average vintage within manufacturer		4.657***		0.002		0.137
		(0.262)		(0.003)		(0.084)
β_2, average vintage between manufacturers		1.736***		1.109***		6.829***
		(0.381)		(0.175)		(0.706)
Constant	617.112***	612.562***	403.189***	403.503***	1450.485***	1465.583***
	(4.950)	(4.823)	(3.986)	(4.021)	(8.646)	(8.253)
Own Vintage Spline	yes	yes	yes	yes	yes	yes
Month-Fixed Effect	yes	yes	yes	yes	yes	yes
Model-Fixed Effect	yes	yes	yes	yes	yes	yes
Adj. R-Squared (within group)	0.317	0.326	0.115	0.115	0.101	0.098
Observations	64,794	64,859	45,324	45,305	181,277	181,449

Note: The table reports the results from estimating equation 9 without the interaction effects for clothes dryers, room airconditioners, and refrigerators. Columns (1), (3) and (5) estimate the effects of within- and between-brands average vintage, and (2), (4) and (6) estimate the effects of within- and between-manufacturer average vintage on price. Clustered standard errors are in parentheses. We use restricted cubic splines with 5 knots in estimating the spline function of vintage.

10 Conclusion

Recent imposition of more stringent energy efficiency standards on durable goods has spurred debate about whether such policies are in consumers' best interests. On the one hand, some argue that standards can address inefficiencies that derive from consumer behavioral anomalies that cause people to underinvest in energy efficiency. Firms, recognizing consumers' unwillingness to invest in energy-saving products, produce fewer efficient products. Firms' incentives to innovate may be further attenuated by partial nonexcludability of new technologies. On the other hand, some believe that standards unnecessarily constrain consumer choice and increase production costs, ultimately reducing consumer welfare. Apparent underinvestment in energy efficiency may derive from unobserved quality characteristics that are associated with energy efficiency, or perhaps because people are credit constrained, not because people overweigh more salient up-front costs compared to less salient future energy-related operating costs.

In this study we approach the issue from a different vantage point. Instead of trying to assess consumer choice, we attempt to assess the implications of actual standard changes on market outcomes. While standard changes provide some pre-post basis for comparison, and we construct a kind of quasi experiment using refrigerators as a control, we acknowledge that the study design is imperfect. For one, standard changes were announced and anticipated well before they were implemented, and the evidence strongly suggests that the policy affected the control.

Despite these design imperfections, the data show remarkable declines in constant-quality prices of washers and refrigerators, and particularly so around the times of policy changes. The coincidence of policy changes with sharp price declines, quality increases, and product entry and exit strongly suggest a causal link. Over a time period with a series of markedly stricter efficiency standards, we estimate consumer welfare improvement of about \$342 per washer assuming quasi-linear utility, and lower bound of \$330 improvement based on a constant-quality Slutsky compensation measure. Difference-in-differences estimates, which may suffer from large spillover effects, suggest that imposing more stringent energy efficiency standards will have, at worst (i.e., assuming no spillover), a negligible effect on consumer welfare.

It is generally very difficult to square these observations with an argument that efficiency standards cause a great burden to consumers. At the same time, these findings suggest that existence of significant benefits from standards that are quite different from those that may have been intended. The standards may be acting to make heterogeneous products somewhat more homogeneous, and thereby increasing competition as theorized by Ronnen (1991). The standards may also facilitate innovation—accelerated creative destruction—that would not have taken place otherwise. Of course, firm profits may have declined as a result of the policy changes, an aspect of the issue we do not address in this paper.

If all of these apparent effects hold up to further scrutiny, it suggests energy-consuming durable goods connect to multiple market failures, including pollution externalities, behavioral anomalies, imperfect competition and public-good aspects of innovation. While stricter standards may help to improve matters in some cases, it is also generally understood that efficient policy requires as many instruments as market failures. Nor does our analysis provide any indication of what an efficient standard would look like from the vantage point of the second best. Thus, one possible direction for future work would be to develop a structural model of appliance markets akin to Berry et al. (1995). If such a model could be estimated and validated against further quasi-experimental interventions, then more thorough policy implications might be derived.

Aside from a novel examination of energy efficiency standards, we present simple and transparent method for evaluating price and quality changes over time. This method may be useful for price indexing in other contexts, assuming availability of suitable data. For example, economists have long noted that the Consumer Price Index (CPI) may exaggerate inflation because the Bureau of Labor Statistics employs methods that cannot fully account for changes in quality (Hausman, 2003). The bias resulting from not fully accounting for quality adjustments and introduction new products could be substantial. Bils (2009) estimates that the quality bias from introducing new models equals two-thirds of nominal price increases. At least for products with identifiable model numbers and overlapping lifetimes, the methods used here might help to improve construction of price indices.

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Appendix A List of Manufacturers and Brand in the NDP Data

Table 8: List of Manufacturers and their Respective Brand

Manufacturer	Brands	
Whirlpool	Amana	Magic Chef
	Estate	Maytag
	Inglis	Roper
	KitchenAid	Whirlpool
General Electric	Ariston	
	GE	
	GE Profile	
	Hotpoint	
Electrolux	Electrolux	
	Frigidaire	
	Westinghouse	
	White Westinghouse	
LG	LG	
Others	Asko	Fagor
	Avanti Pro	Fisher & Paykel
	Bosch	Haier
	Danby	Miele
	Electro Brand	Speed Queen
	Equator Appliances	Summit
	Eurotec	

Note: The table lists the four major clothes washer manufacturers in the US (based on their market share) and their respective brands and subsidiaries. Three of the major manufacturers sell clothes washers under four or more brands.

Appendix B Robustness Check

To address the potential bias introduced by including the 35% masked models in the data, we conduct a series of robustness checks. This include repeating all the important figures in the analysis and the regressions of price against the average vintage within and between firms, both at the brand and manufacturer levels (equation 8). The results from estimating equation 8 without masked models are presented in Table 9. We find the our qualitative results remain the same. Meanwhile, the figure representing the average and constant-quality price trends without masked models is presented in Figure 13. We also find no significant influence of excluding masked models on the price trends, both the market average price and the constructed CQPI.

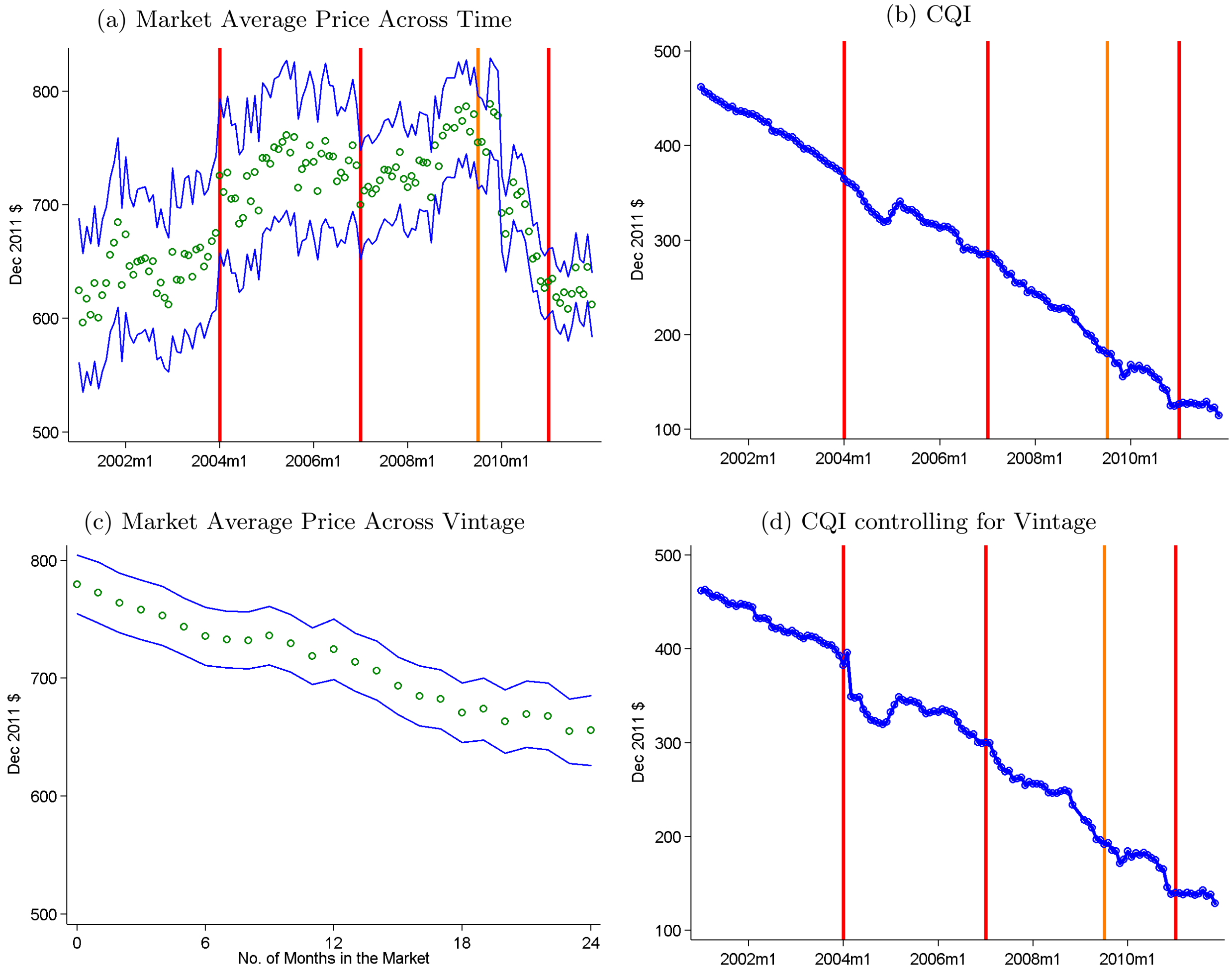
Table 9: Results from regressing real price of a washer model at a particular time period (Unmasked Models only)

	(1)	(2)
β_1, average vintage *within brand*	2.007***	
	(0.456)	
β_2, average vintage *between brands*	4.011***	
	(0.775)	
β_1, average vintage *within manufacturer*		3.817***
		(0.468)
β_2, average vintage *between manufacturers*		1.083*
		(0.561)
Constant	700.737***	664.264
	(142.630)	(140.270)
Own Vintage Spline	yes	yes
Month-Fixed Effect	yes	yes
Model-Fixed Effect	yes	yes
Adj. R-Squared (within group)	0.373	0.372
Observations	22,445	22,755

Notes: The table reports the results from estimating equation 9 without the interaction effects *using unmasked models only*. Columns (1) estimates the effects of within- and between-brands average vintage, and (2) estimates the effects of within- and between-manufacturer average vintage on price. Clustered standard errors are in parentheses. We use restricted cubic splines with 5 knots in estimating the spline function of vintage.

Source of data: The NPD Group.

Figure 13: Market Average and Within-Model Price Trends *without Masked Models*

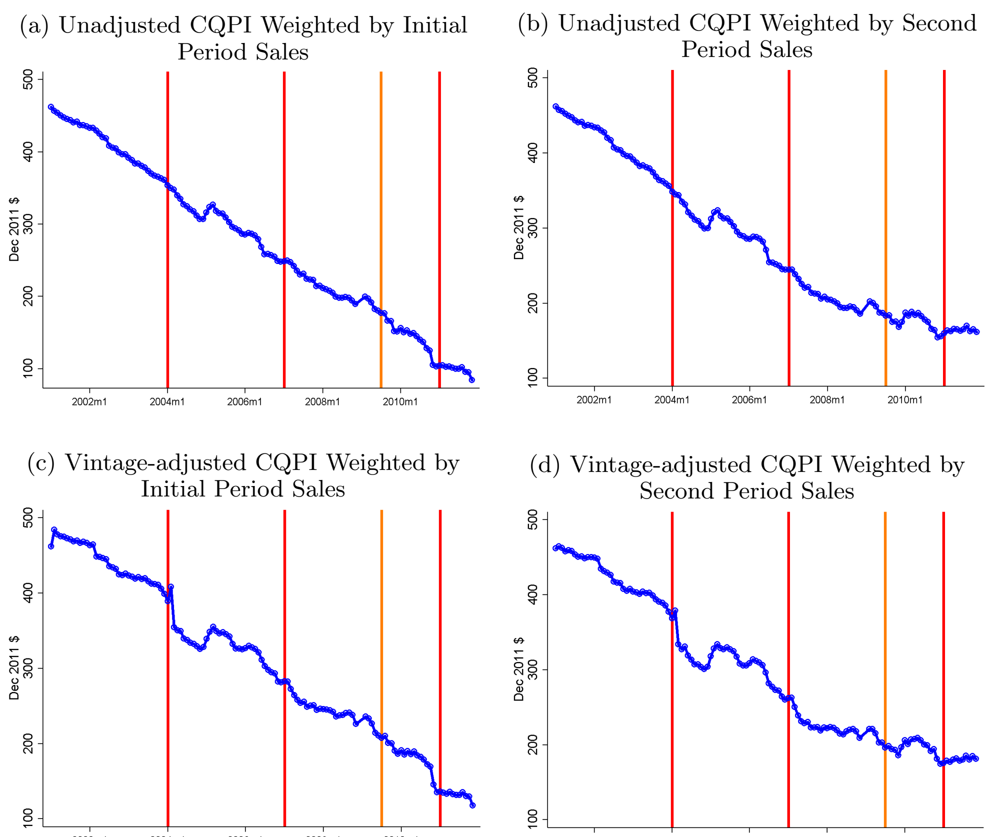


Note: The figure shows the price trends, both on the average (left-hand panels) and within-model (right hand panels) *using unmasked models only*. Each point represents either average price or average price change, with the blue line representing the 95% confidence interval. The solid red vertical line represent the effective date of simultaneous policy changes in the federal minimum energy efficiency standard and Energy Star standard, while the orange vertical line is for the Energy Star policy update that took effect in July 2009. Panels (a) & (c) shows market average price trends across time (between 2001 and 2011) and product vintage, respectively. Panels (b) & (d) shows the within-model price change relative to Jan 2001 average price, which was \$621.93. Points in panels (b) & (d) are essentially coefficients of each month-year dummy generated from running a regression with product-fixed-effect of a model's price at a particular time period. All prices are in December 2011 US dollars.

Appendix C The CQPI Under Weights

One concern about the CQPI is that the weights are endogenous. Consumers may substitute toward products with lower prices, causing a bias in the overall trend. If we were to weight price changes by the initial period of the difference, the bias would most likely be positive, as models discounted in the initial period would presumably rise in price and be weighted more heavily. Conversely, if we were to weight by the second period then models discounted in the second period would presumably see a larger price decline while sales increased, biasing the overall trend downward. We therefore weight the two periods equally. In this section, we weight the CQPI by the initial and second period sales. We find no noticeable influence on the CQPI under different weighting schemes.

Figure 14: CQPI Under Different Weights



Notes: Panels (a) & (b) show the unadjusted CQPI weighted by initial and second period sales, respectively. Panel (c) & (d) show the CQPI adjusted for product vintage, estimated from a fixed effects regression model, and weighted by initial and second period sales, respectively. The solid red vertical line represents the effective date of simultaneous policy changes in the federal minimum energy efficiency standard and Energy Star certification threshold, while the orange vertical line is for the Energy Star threshold change that took effect in July 2009. All prices are in December 2011 US dollars.

Appendix D Average Effect of Policy Change (3-month Period)

To check the robustness of the estimated average effect of a policy change (Table 4), we estimate equation 7 with an assumption that the effect of the policy change occurs within a 3-month pre- and post-policy change. For example, for 2004 policy change, we believe that the effect of the announcement started to take place in October 2003 up to March 2004. We then compare this with the observations starting from April 2002 (i.e. two-year period). Table 10 summarizes the results of the regression for the percentage change in the CQPI, quality index and level change in estimated welfare. Columns labeled (1) pertain to the standard DID; (2) includes year-month fixed effect to control for potential idiosyncratic shocks in each time period; and (3) includes the intersection of month and refrigerator dummies to control for the fairly robust seasonality that we observed for refrigerators in each of the key variable. Results are qualitatively similar with what we find using the 6-month pre- and post-implementation period.

Table 10: Results from Estimating the Average Effect of the Policy Change.

	Dependent Variable								
Variables	**%Δ CQPI**			**%Δ Quality**			**Δ Welfare**		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Treatment	-0.045	0.042	0.132	0.182	-0.048	4.656**	-1.610*	-1.841**	-0.757
	(0.251)	(0.206)	(0.697)	(0.672)	(0.622)	(2.181)	(0.906)	(0.741)	(2.435)
Policy Dummy	-0.724*	-0.028	1.417	0.704	-11.431***	-15.769**	3.705	0.332	0.227
	(0.437)	(0.574)	(1.392)	(1.719)	(3.220)	(3.113)	(2.351)	(3.038)	(6.300)
Treatment x Policy	**-0.876**	**-0.963**	**-0.892**	**-0.148**	**0.082**	**-0.076**	**0.193**	**0.424**	**-0.581**
	(0.880)	**(0.707)**	**(0.635)**	**(1.828)**	**(1.934)**	**(1.625)**	**(3.305)**	**(2.207)**	**(2.058)**
Constant	-0.599***	0.422**	-1.214	0.911	13.370***	16.097	3.551***	-0.291	1.738
	(0.145)	(0.206)	(1.002)	(0.603)	(0.622)	(3.010)	(0.766)	(0.741)	(2.932)
Year-month fixed effect	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Month x ref dummy	No	No	Yes	No	No	Yes	No	No	Yes
R-squared	0.056	0.707	0.783	0.003	0.560	0.799	0.048	0.743	0.816
Adj. R-squared	0.044	0.391	0.506	-0.009	0.087	0.543	0.037	0.468	0.581
Observations	254	254	254	254	254	254	254	254	254

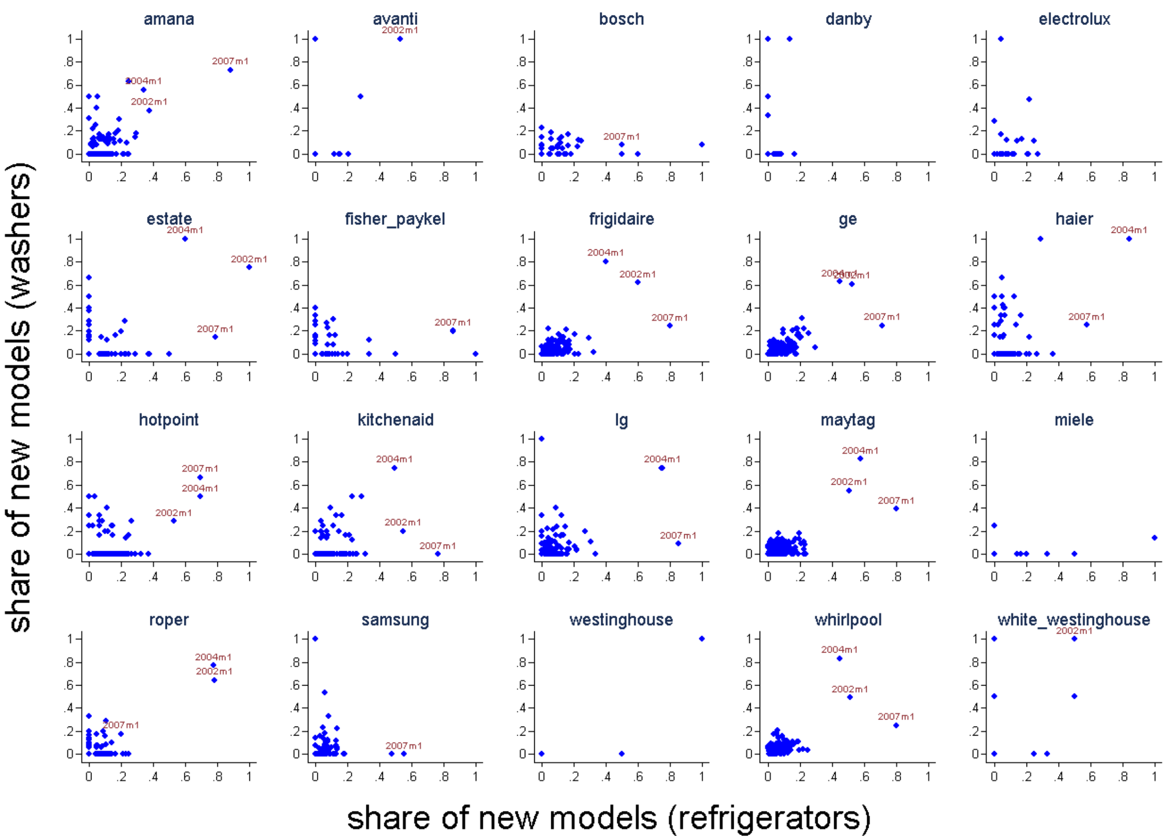
Note: The table presents the results from estimating equation 7, which yields the average effect of the policy change on trend in CQPI, Quality Index and estimated welfare change. Treatment is a dummy variable equal to one if the observation is for the appliance that is affected by the standard (i.e. clothes washer); Policy is a dummy variable that turns on at the time the new standard is perceived to have effect on our key variables. We assume that the effect of the policy took place *within the 3-month pre- and post-policy change*. For example, the 2004 policy change, due to its anticipatory nature, is perceived to have effect starting October 2003 up to March 2004. We then compare this with the observations starting from April 2002 (i.e. two-year period). Columns labeled (1) pertain to the standard difference-in-difference (DID) approach; (2) includes year-month fixed effect to control for potential idiosyncratic shocks in each time period; and (3) includes the intersection of month and refrigerator dummies to control for the fairly robust seasonality that we observed for refrigerators in each of the key variable. Robust standard errors are in parentheses. *, **, *** represent statistical significance at 10, 5, and 1 percent level, respectively.

Sources of Data: The NPD Group, authors' calculations.

Appendix E Correlation in the introduction of new models between clothes washers and refrigerators at the brand level

We observe that unit price (holding quality constant), quality and consumer welfare gains for clothes washers and refrigerators follow similar trends and fluctuations, including the significant drop around 2004 policy change. In order to get a sense of the potential factor that might influence the correlated effect, we look at the correlation in the share of new models to the total stock of units in a particular time period between clothes washers and refrigerators. At the manufacturer level, we find significant correlation in introducing new models between clothes washers and refrigerators right around the policy change in 2004 and 2007. We did the same exercise at the brand level and find the same significant correlation particularly for major brands of washers and refrigerators like GE, LG, Maytag, and Whirlpool (Figure 15).

Figure 15: Correlation in the share of new models to total stock units between washers and dryers, brand level, monthly, 2001-2011.



Source of data: The NPD Group.

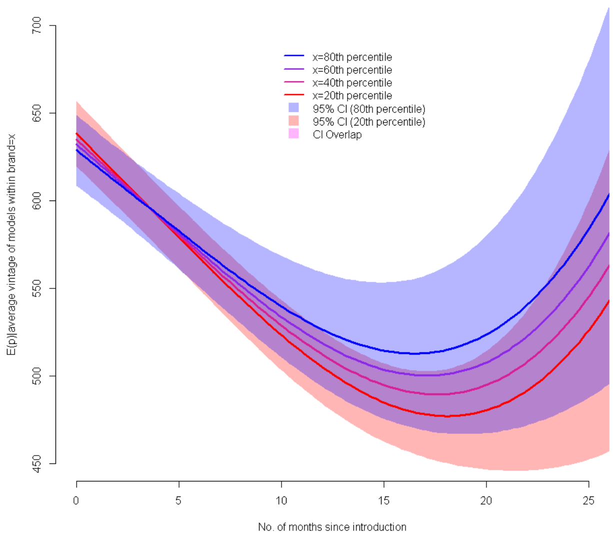
Appendix F Within and Between Brands Competition and Price Trends for Clothes Washers

We use the estimates from equation 9 to predict the price trend of typical clothes washer holding average vintage of models within brands constant. Figure 16 plots this predicted price across the first two years of a clothes washer in the market, holding *within-brand* average vintage equivalent to about 8 months (20th percentile), 11 months (40th percentile), 13 months (60th percentile) and 17 months (80th percentile), while Figure 17 plots the predicted price holding average vintage of models *between brands* constant at about 10 months (20th percentile), 12 months (40th percentile), 14 months (60th percentile), and 15 months (80th percentile).

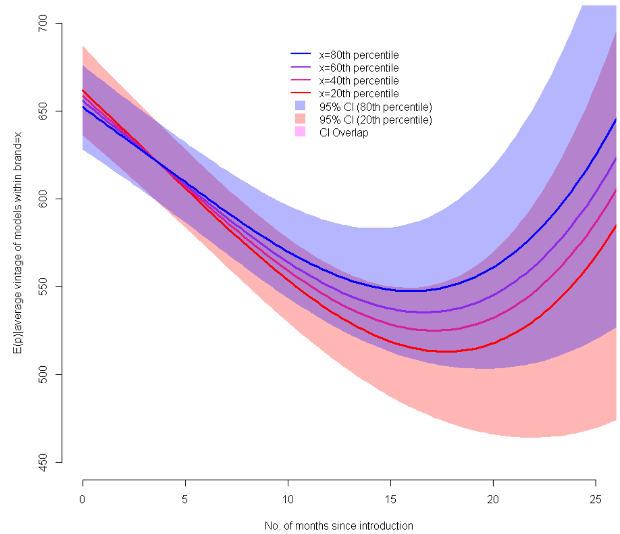
We also predict the price trend of a typical washer at different average vintage *within the same manufacturer* and *between manufacturers.* Figure 18 shows the predicted price of a typical clothes washer, holding average vintage of models *within the same manufacturer* constant at about 9 months (20th percentile), 11 months (40th percentile), 13 months (60th percentile) and 16 months (80 percentile). Figure 19 plots the predicted price at *between-manufacturers* average vintage equivalent to 9 months (20th percentile), 13 months (40th percentile), 16 months (60th percentile) and 19 months (80 percentile).

Figure 16: Life Cycle Pricing of Clothes Washers Under Different Within-Brand Average Vintage

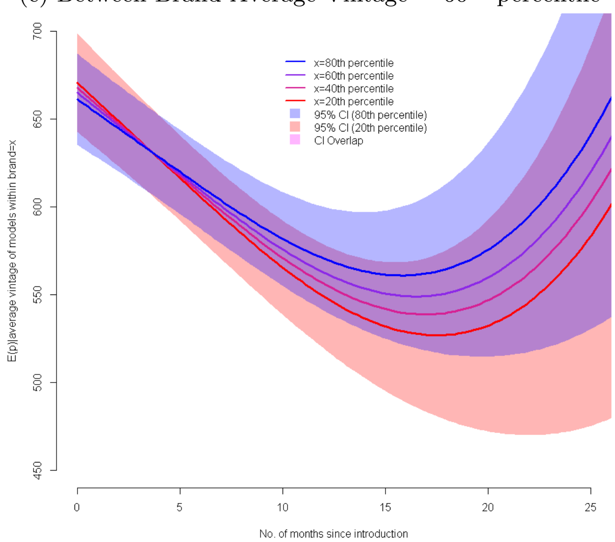
(a) Between Brand Average Vintage = 20^{th} percentile



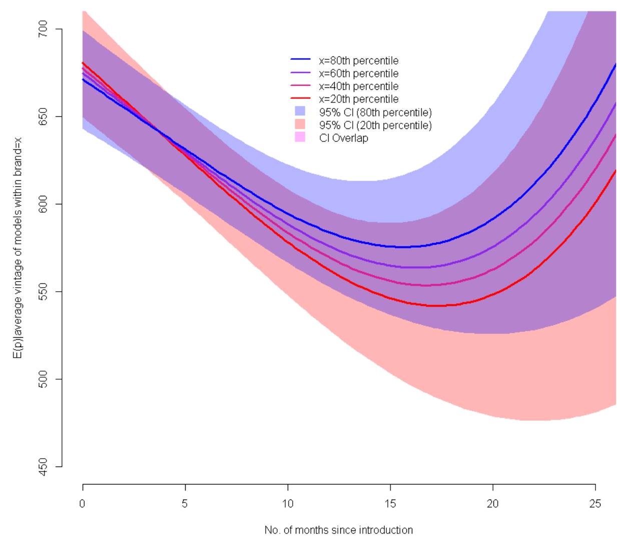
(b)Between Brand Average Vintage = 40^{th} percentile



(c) Between Brand Average Vintage = 60^{th} percentile



(d) Between Brand Average Vintage = 80^{th} percentile

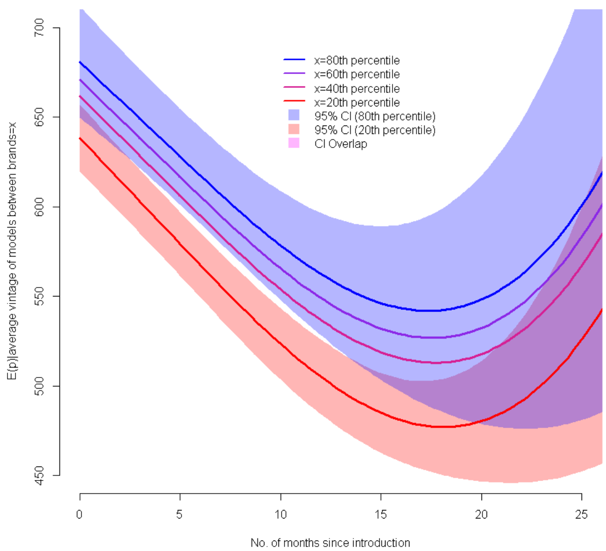


Note: The figure shows that trend in the predicted price of a representative clothes washer using equation 9 during its first two years. We estimate equation 9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a within-brand average vintage of clothes washer. The 20th, 40th, 60th and 80th percentile of within-brand average vintage correspond to 7.71, 10.67. 13.32 and 16.58, respectively. For the between-brand average vintage, the 20th, 40th, 60th and 80th percentile correspond to 9.62, 12.54, 13.67, and 14.90, respectively.

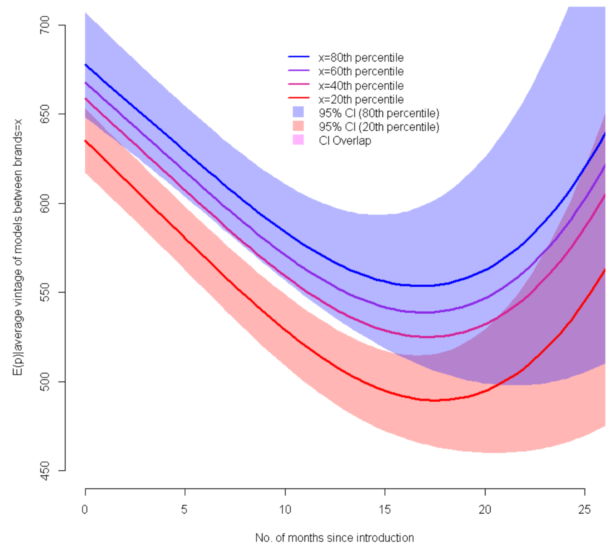
Source: The NPD Group; authors' calculation.

Figure 17: Life Cycle Pricing of Clothes Washers Under Different Between-Brands Average Vintage

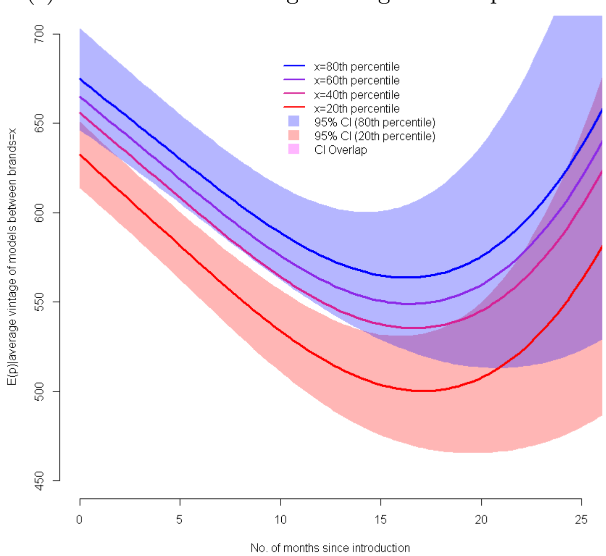
(a) Within Brand Average Vintage = 20^{th} percentile



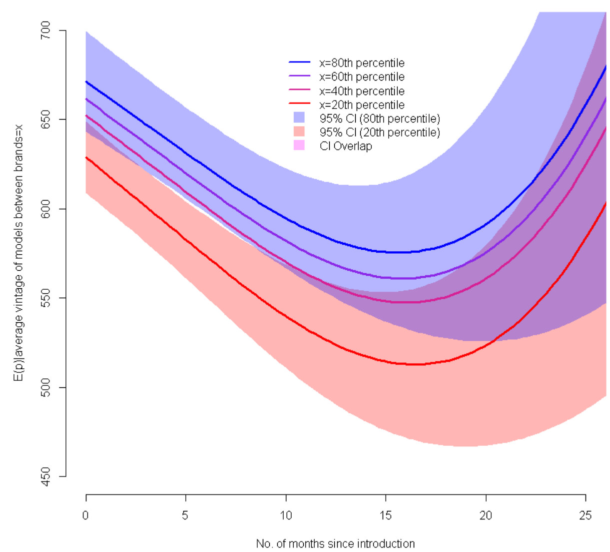
(b)Within Brand Average Vintage = 40^{th} percentile



(c) Within Brand Average Vintage = 60^{th} percentile



(d) Within Brand Average Vintage = 80^{th} percentile

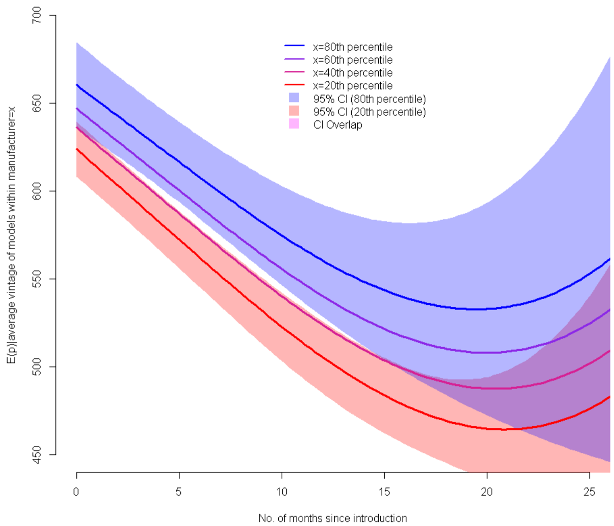


Note: The figure shows that trend in the predicted price of a representative clothes washer using equation 9 during its first two years. We estimate equation 9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a between-brand average vintage of clothes washer. The 20th, 40th, 60th and 80th percentile of within-brand average vintage correspond to 9.62, 12.54, 13.67, and 14.90, respectively. For the between-brand average vintage, the 20th, 40th, 60th and 80th percentile correspond to 7.71, 10.67. 13.32 and 16.58, respectively.

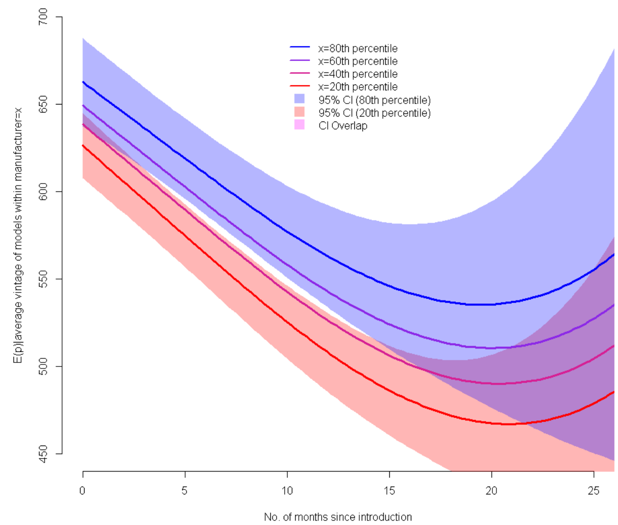
Source: The NPD Group; authors' calculation.

Figure 18: Life Cycle Pricing of Clothes Washers Under Different Within-Manufacturer Average Vintage

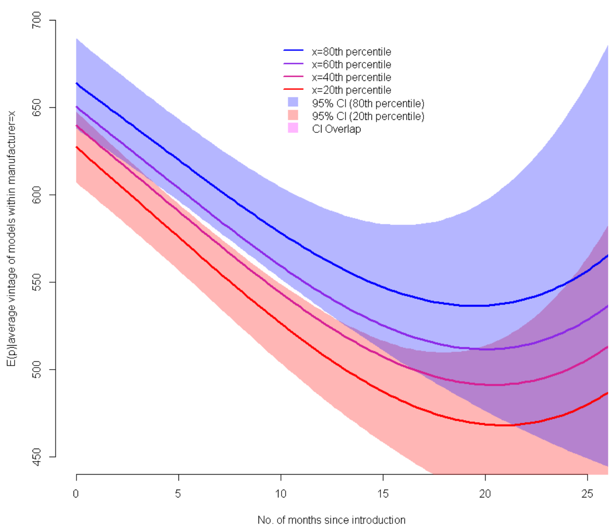
(a) Between Manufacturer Average Vintage = 20^{th} percentile



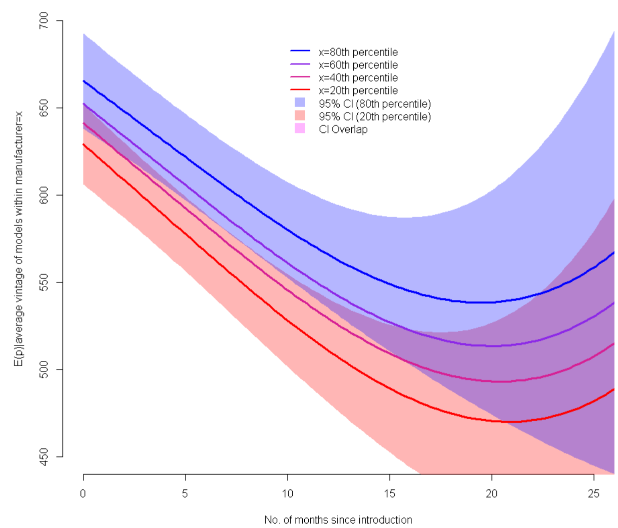
(b)Between Manufacturer Average Vintage = 40^{th} percentile



(c) Between Manufacturer Average Vintage = 60^{th} percentile



(d) Between Manufacturer Average Vintage = 80^{th} percentile

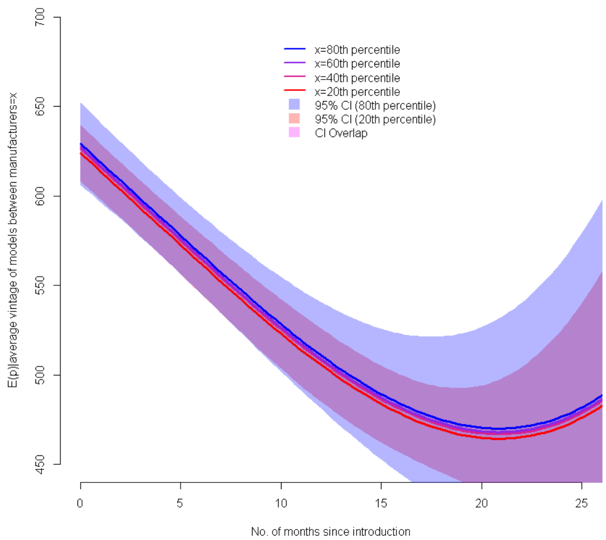


Note: The figure shows that trend in the predicted price of a representative clothes washer using equation 9 during its first two years. We estimate equation 9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a within-manufacturer average vintage of clothes washer. The 20th, 40th, 60th and 80th percentile of within-manufacturer average vintage correspond to 8.86, 11.14, 13.18, and 15.68, respectively. For the between-manufacturer average vintage, the 20th, 40th, 60th and 80th percentile correspond to 9.47, 12.53, 13.85, and 16.12, respectively.

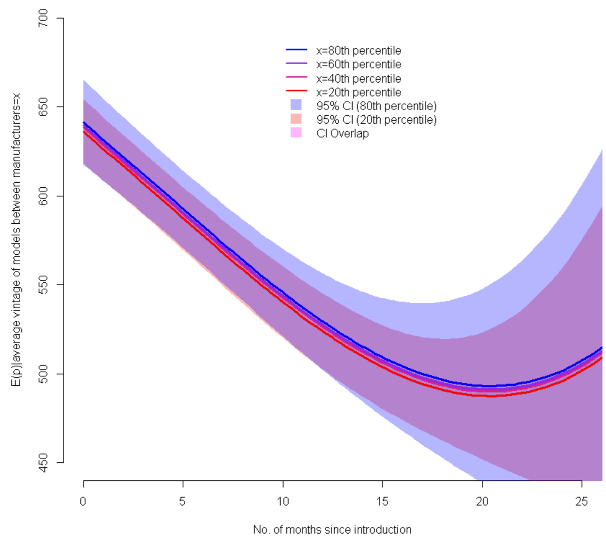
Source: The NPD Group; authors' calculation.

Figure 19: Life Cycle Pricing of Clothes Washers Under Different Between-Manufacturers Average Vintage

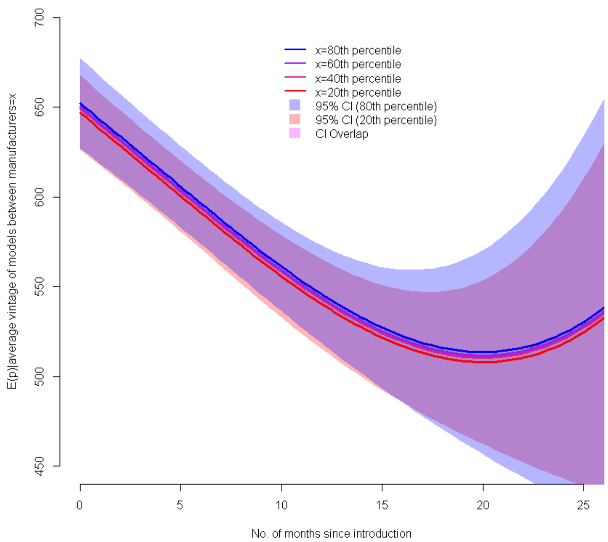
(a) Within Manufacturer Average Vintage = 20^{th} percentile



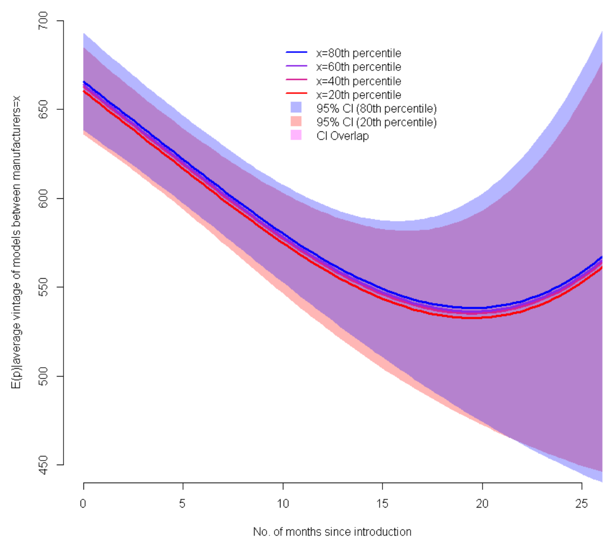
(b) Within Manufacturer Average Vintage = 40^{th} percentile



(c) Within Manufacturer Average Vintage = 60^{th} percentile



(d) Within Manufacturer Average Vintage = 80^{th} percentile



Note: The figure shows that trend in the predicted price of a representative clothes washer using equation 9 during its first two years. We estimate equation 9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a between-manufacturer average vintage of clothes washer. The 20th, 40th, 60th and 80th percentile of between-manufacturer average vintage correspond to 9.47, 12.53, 13.85, and 16.12, respectively. For the within-manufacturer average vintage, the 20th, 40th, 60th and 80th percentile correspond to 8.86, 11.14, 13.18, and 15.68, respectively.

Source: The NPD Group; authors' calculation.

G Within and Between Brands Competition and Price Trends for Clothes Dryers, Room Airconditioner and Refrigerators

To see if cannibalism is unique to the appliance that had more stringent energy efficiency standards over the sample period (i.e. clothes washer), we use refrigerator, room AC and clothes dryer as counterfactuals. None of these appliances had adopted or implemented a simultaneous minimum energy efficiency standards and Energy Star certification change during the study period. This section plots predicted price using estimates from equation 9 for these appliances.

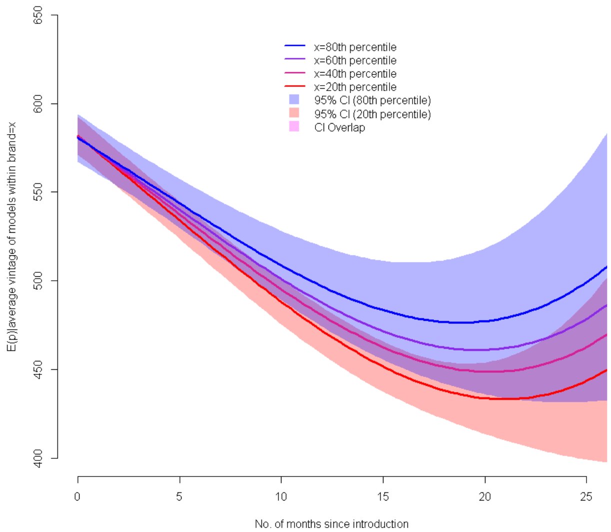
G.1 Clothes Dryers

We use the estimates from equation 9 to predict the price trend of typical clothes dryer holding average vintage of models within brands constant. Figure 16 plots this predicted price across the first two years of a clothes dryer in the market, holding within-brand average vintage equivalent to about 8 months (20th percentile), 11 months (40th percentile), 14 months (60th percentile) and 17 months (80th percentile), while Figure 17 plots the predicted price holding average vintage of models *between brands* constant at about 10 months (20th percentile), 12 months (40th percentile), 14 months (60th percentile), and 16 months (80th percentile).

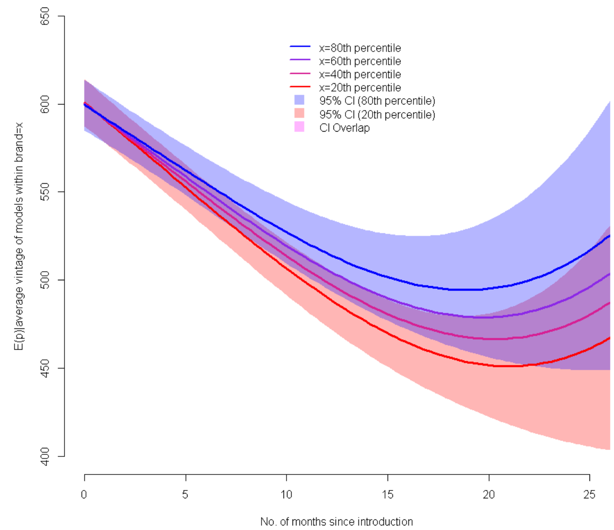
We also predict the price trend of a typical washer at different average vintage within the same manufacturer and between manufacturers. Figure 18 shows the predicted price of a typical clothes dryer, holding average vintage of models within the same manufacturer constant at about 10 months (20th percentile), 13 months (40th percentile), 15 months (60th percentile) and 17 months (80 percentile). Figure 19 plots the predicted price at between-manufacturers average vintage equivalent to 9 months (20th percentile), 12 months (40th percentile), 14 months (60th percentile) and 17 months (80 percentile).

Figure 20: Life Cycle Pricing of Clothes Dryers Under Different Within-Brand Average Vintage

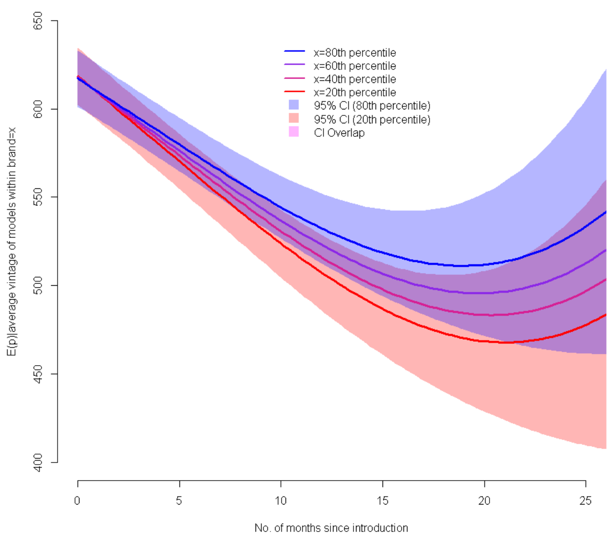
(a) Between Brand Average Vintage = 20^{th} percentile



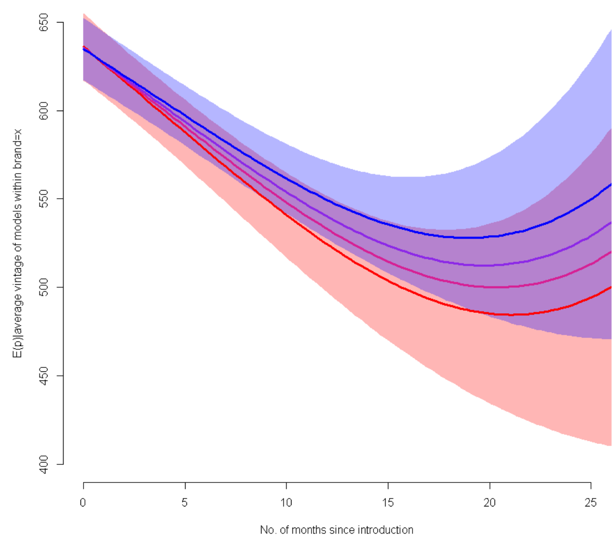
(b)Between Brand Average Vintage = 40^{th} percentile



(c) Between Brand Average Vintage = 60^{th} percentile



(d) Between Brand Average Vintage = 80^{th} percentile

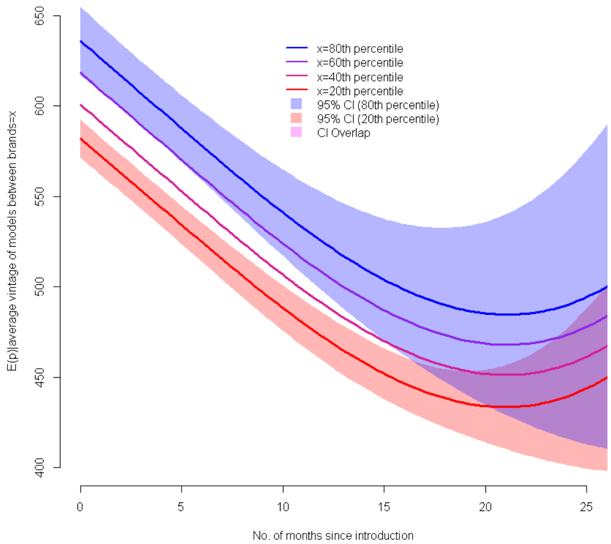


Note: The figure shows the trend in the predicted price of a representative clothes dryer using equation 9 during its first two years. We estimate equation 9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a within-brand average vintage of clothes dryer. The 20th, 40th, 60th and 80th percentile of within-brand average vintage correspond to 8,17, 11.38, 14.04 and 17.52, respectively. For the between-brand average vintage, the 20th, 40th, 60th and 80th percentile correspond to 10.12, 12.40, 14.54, and 16.67, respectively.

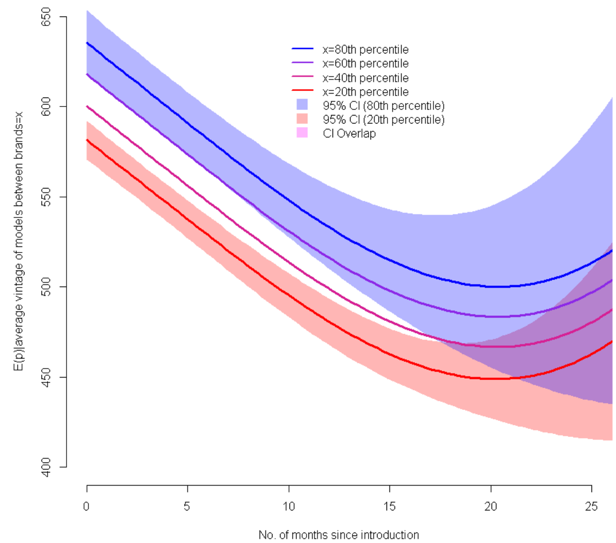
Source: The NPD Group; authors' calculation.

Figure 21: Life Cycle Pricing of Clothes Dryers Under Different Between-Brand Average Vintage

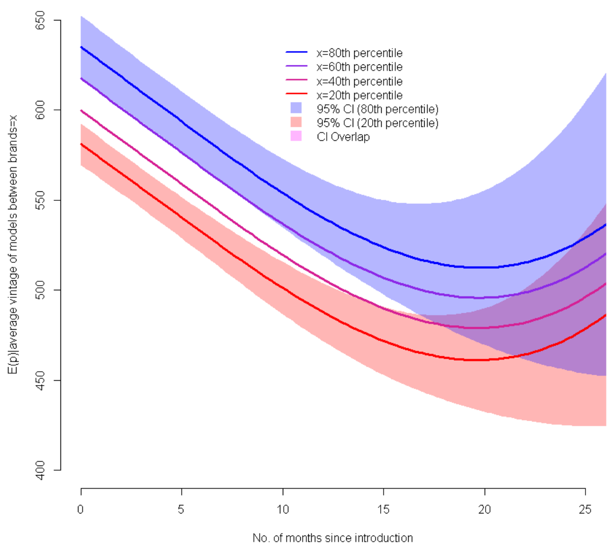
(a) Within Brand Average Vintage = 20^{th} percentile



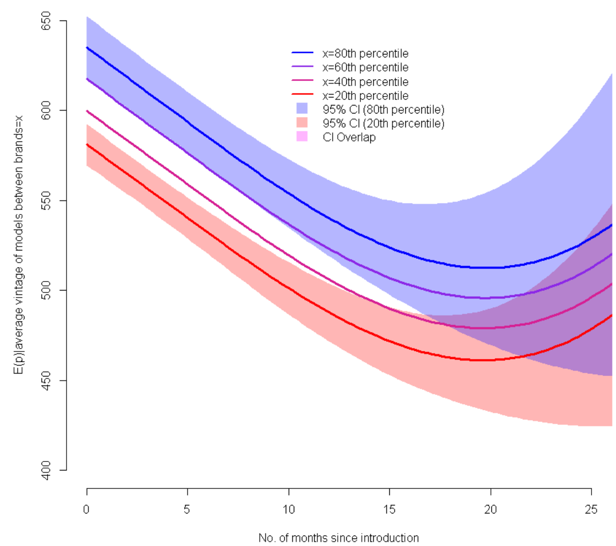
(b)Within Brand Average Vintage = 40^{th} percentile



(c) Within Brand Average Vintage = 60^{th} percentile



(d) Within Brand Average Vintage = 80^{th} percentile

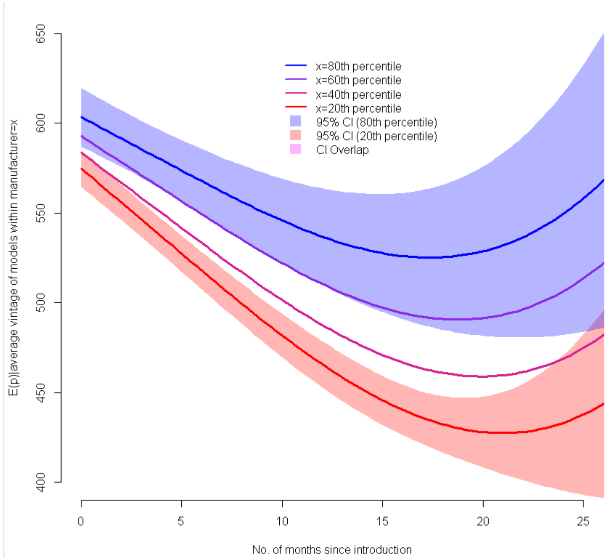


Note: The figure shows the trend in the predicted price of a representative clothes dryer using equation 9 during its first two years. We estimate equation 9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a between-brand average vintage of clothes dryer. The 20th, 40th, 60th and 80th percentile of within-brand average vintage correspond to 8,17, 11.38, 14.04 and 17.52, respectively. For the between-brand average vintage, the 20th, 40th, 60th and 80th percentile correspond to 10.12, 12.40, 14.54, and 16.67, respectively.

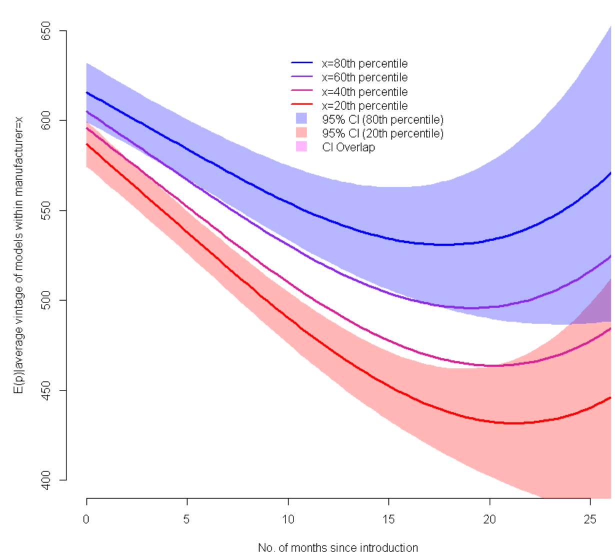
Source: The NPD Group; authors' calculation.

Figure 22: Life Cycle Pricing of Clothes Dryers Under Different Within-Manufacturer Average Vintage

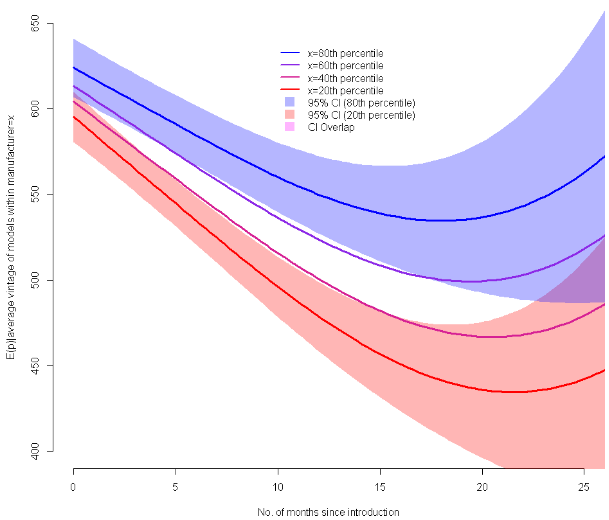
(a) Between Manufacturer Average Vintage = 20^{th} percentile



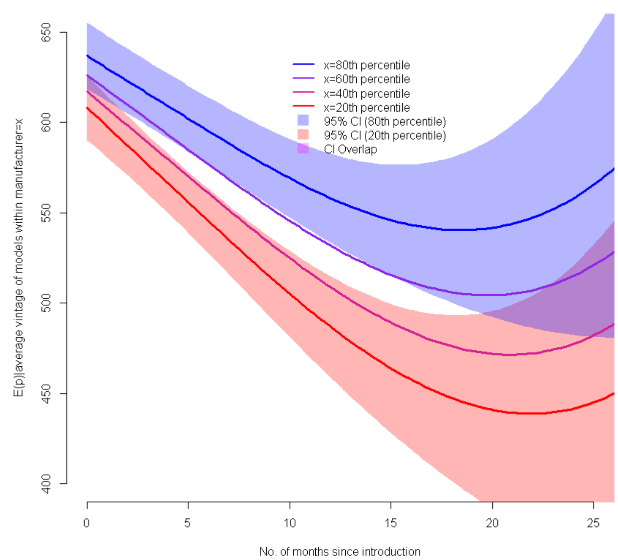
(b)Between Manufacturer Average Vintage = 40^{th} percentile



(c) Between Manufacturer Average Vintage = 60^{th} percentile



(d) Between Manufacturer Average Vintage = 80^{th} percentile

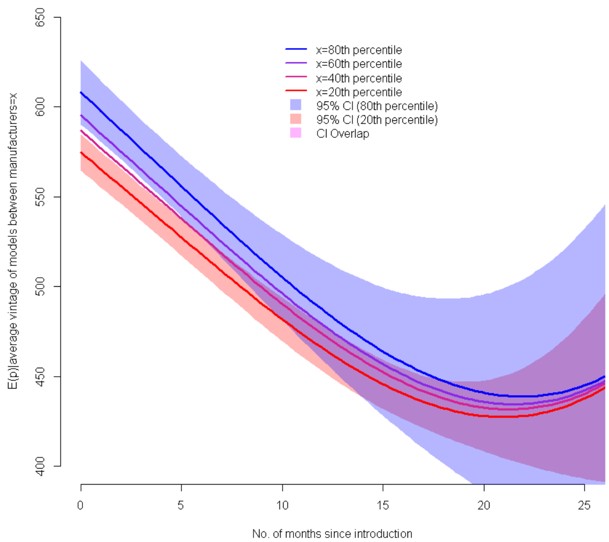


Note: The figure shows the trend in the predicted price of a representative clothes dryer using equation 9 during its first two years. We estimate equation 9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a within-manufacturer average vintage of clothes dryer. The 20th, 40th, 60th and 80th percentile of within-manufacturer average vintage correspond to 8.97, 11.55, 14.25, and 17.35, respectively. For the between-manufacturer average vintage, the 20th, 40th, 60th and 80th percentile correspond to 10.11, 12.91, 14.79, and 17.74, respectively.

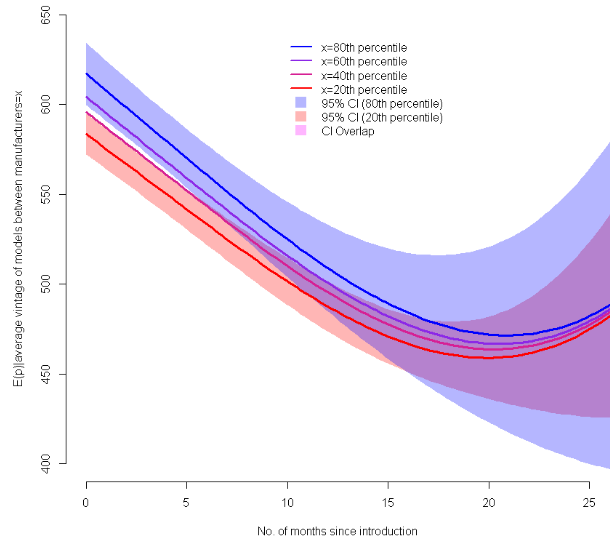
Source: The NPD Group; authors' calculation.

Figure 23: Life Cycle Pricing of Clothes Dryers Under Different Between-Manufacturer Average Vintage

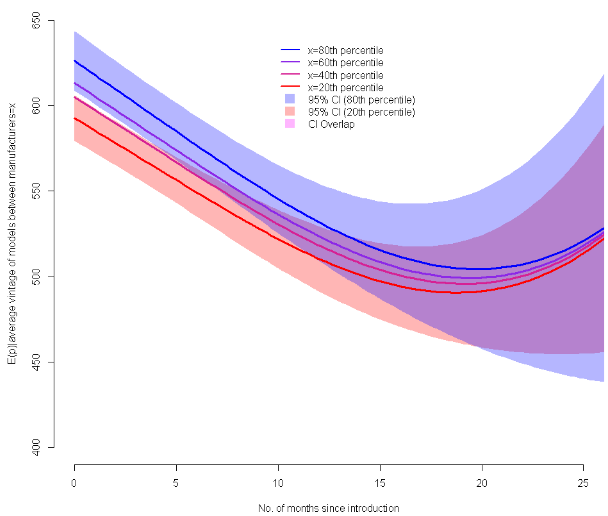
(a) Within Manufacturer Average Vintage = 20^{th} percentile



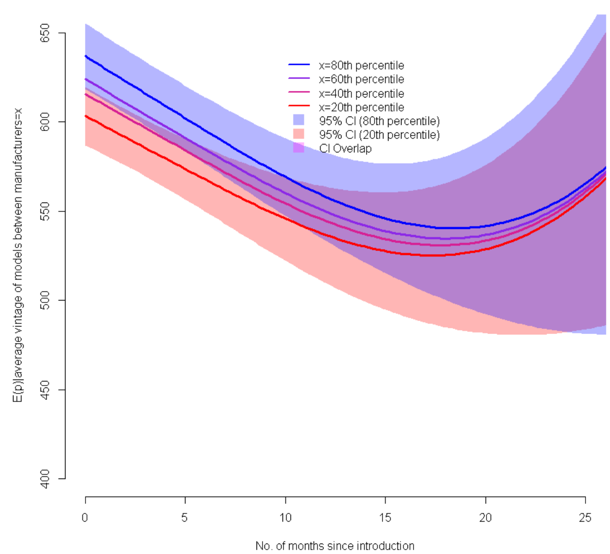
(b) Within Manufacturer Average Vintage = 40^{th} percentile



(c) Within Manufacturer Average Vintage = 60^{th} percentile



(d) Within Manufacturer Average Vintage = 80^{th} percentile



Note: The figure shows the trend in the predicted price of a representative clothes dryer using equation 9 during its first two years. We estimate equation 9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a between-manufacturer average vintage of clothes dryer. The 20th, 40th, 60th and 80th percentile of between-manufacturer average vintage correspond to 10.11, 12.91, 14.79, and 17.74, respectively. For the within-manufacturer average vintage, the 20th, 40th, 60th and 80th percentile correspond to 8.97, 11.55, 14.25, and 17.35, respectively.

Source: The NPD Group; authors' calculation.

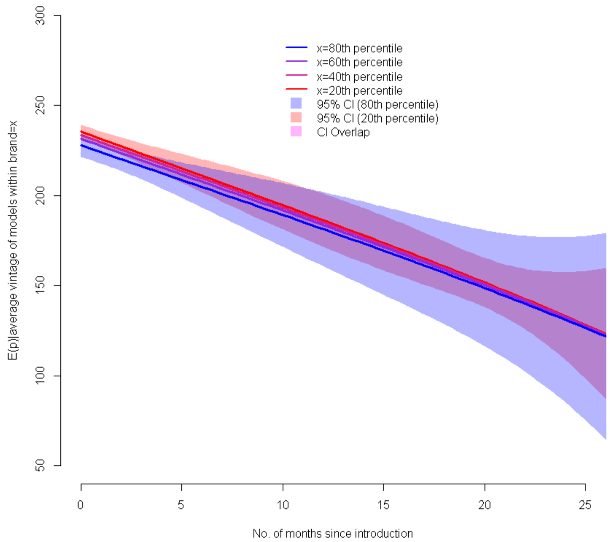
G.2 Room Airconditioners

We use the estimates from equation 9 to predict the price trend of typical room AC holding average vintage of models within brands constant. Figure 16 plots this predicted price across the first two years of a room AC in the market, holding within-brand average vintage equivalent to about 6 months (20th percentile), 9 months (40th percentile), 12 months (60th percentile) and 18 months (80th percentile), while Figure 17 plots the predicted price holding average vintage of models *between brands* constant at about 7 months (20th percentile), 9 months (40th percentile), 11 months (60th percentile), and 15 months (80th percentile).

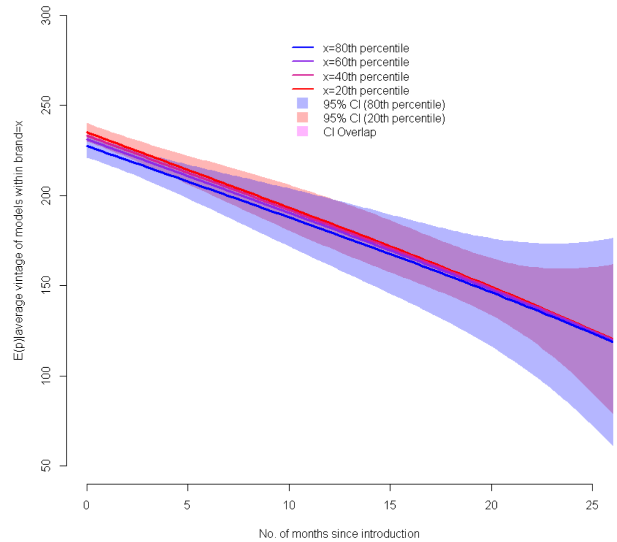
We also predict the price trend of a typical room AC at different average vintage within the same manufacturer and between manufacturers. Figure 18 shows the predicted price of a typical room AC, holding average vintage of models within the same manufacturer constant at about 5 months (20th percentile), 9 months (40th percentile), 13 months (60th percentile) and 19 months (80 percentile). Figure 19 plots the predicted price at between-manufacturers average vintage equivalent to 7 months (20th percentile), 9 months (40th percentile), 11 months (60th percentile) and 15 months (80 percentile).

Figure 24: Life Cycle Pricing of Room ACs Under Different Within-Brand Average Vintage

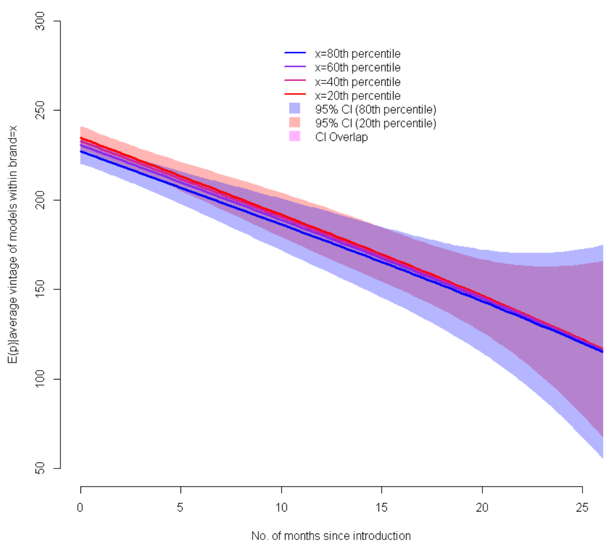
(a) Between Brand Average Vintage = 20^{th} percentile



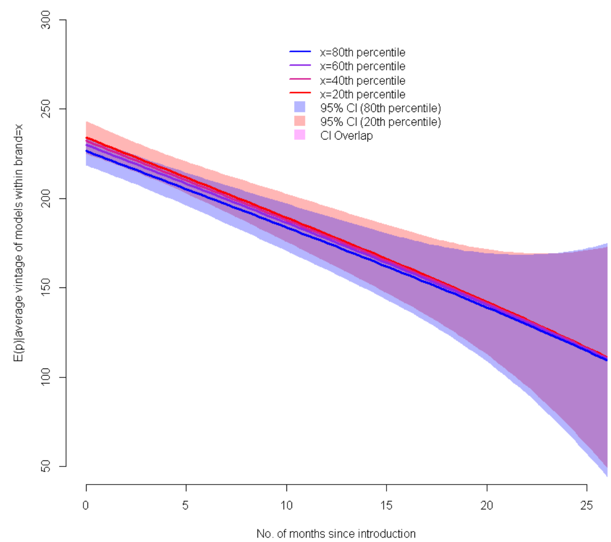
(b)Between Brand Average Vintage = 40^{th} percentile



(c) Between Brand Average Vintage = 60^{th} percentile



(d) Between Brand Average Vintage = 80^{th} percentile

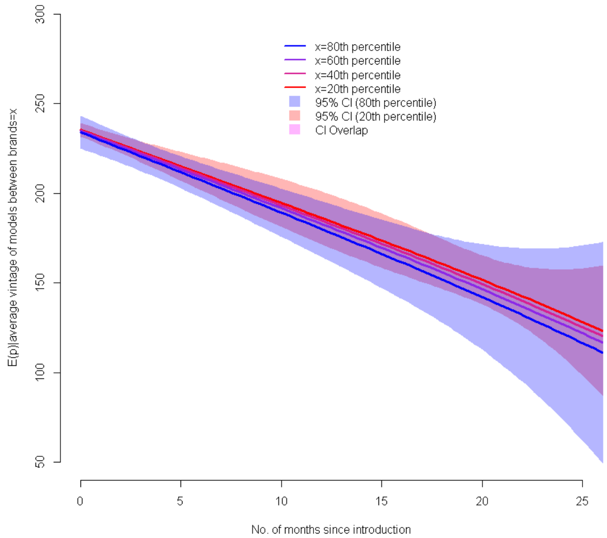


Note: The figure shows the trend in the predicted price of a representative room AC using equation 9 during its first two years. We estimate equation 9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a within-brand average vintage of room AC. The 20th, 40th, 60th and 80th percentile of within-brand average vintage correspond to 5.88, 8.98, 12.50, and 18.38 respectively. For the between-brand average vintage, the 20th, 40th, 60th and 80th percentile correspond to 7.22, 9.08, 11.38, and 14.92 respectively.

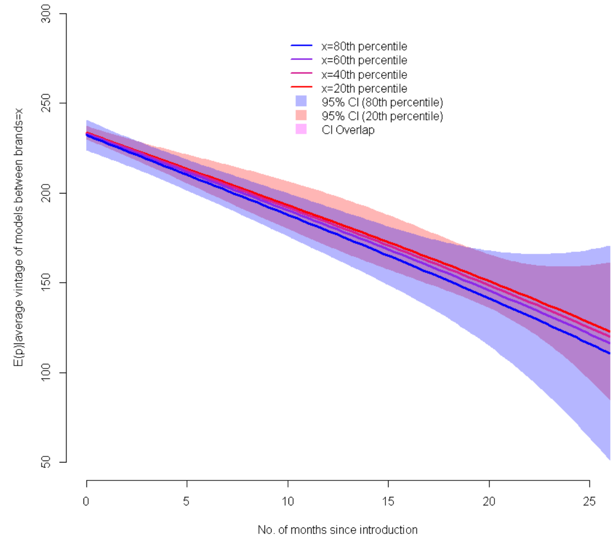
Source: The NPD Group; authors' calculation.

Figure 25: Life Cycle Pricing of Room ACs Under Different Between-Brand Average Vintage

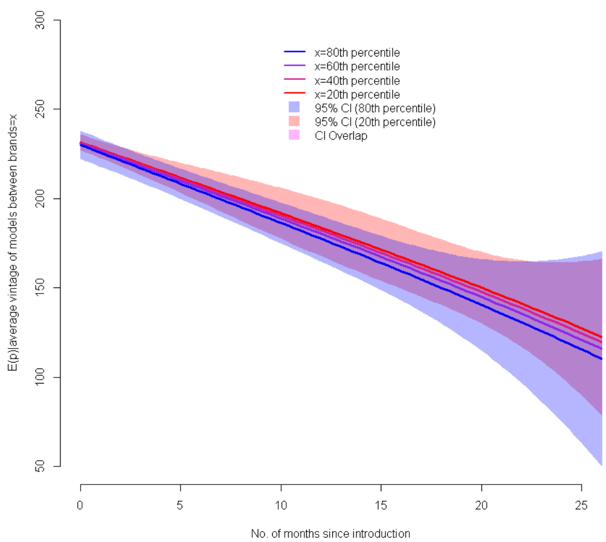
(a) Within Brand Average Vintage = 20^{th} percentile



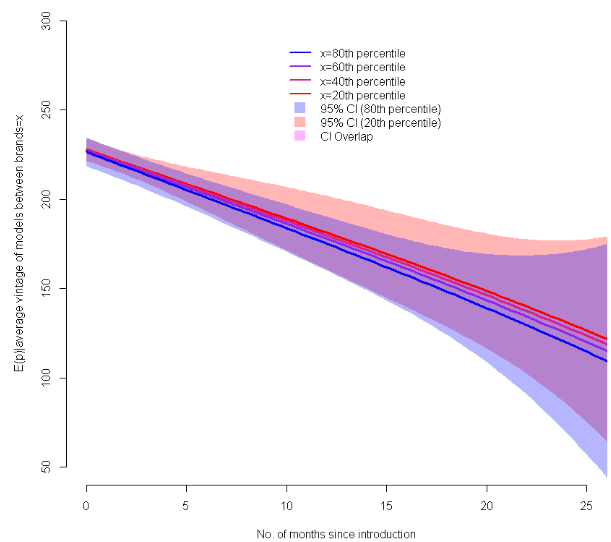
(b)Within Brand Average Vintage = 40^{th} percentile



(c) Within Brand Average Vintage = 60^{th} percentile



(d) Within Brand Average Vintage = 80^{th} percentile

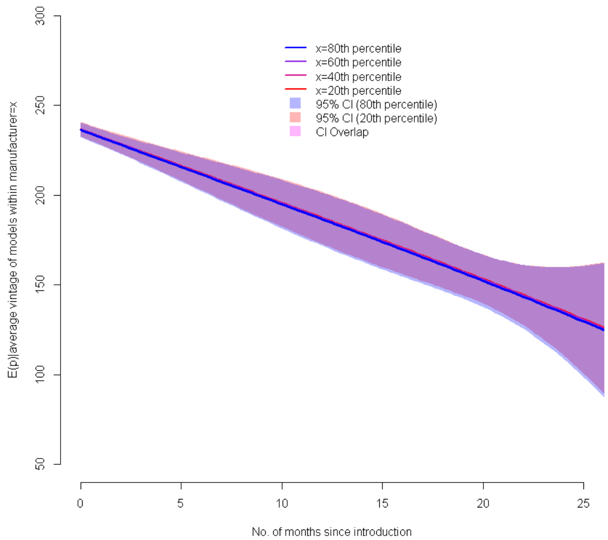


Note: The figure shows the trend in the predicted price of a representative room AC using equation 9 during its first two years. We estimate equation 9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a between-brand average vintage of room AC. The 20th, 40th, 60th and 80th percentile of within-brand average vintage correspond to 5.88, 8.98, 12.50, and 18.38 respectively. For the between-brand average vintage, the 20th, 40th, 60th and 80th percentile correspond to 7.22, 9.08, 11.38, and 14.92 respectively.

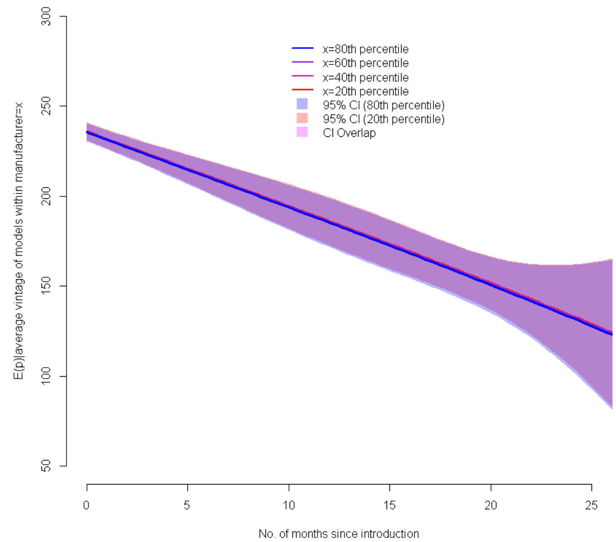
Source: The NPD Group; authors' calculation.

Figure 26: Life Cycle Pricing of Room ACs Under Different Within-Manufacturer Average Vintage

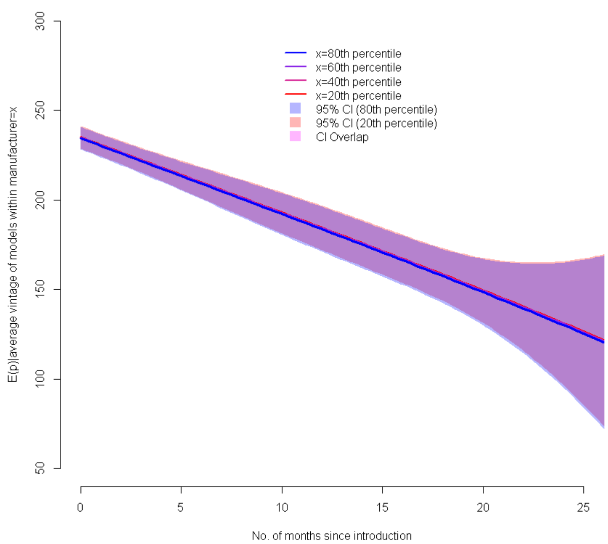
(a) Between Manufacturer Average Vintage = 20^{th} percentile



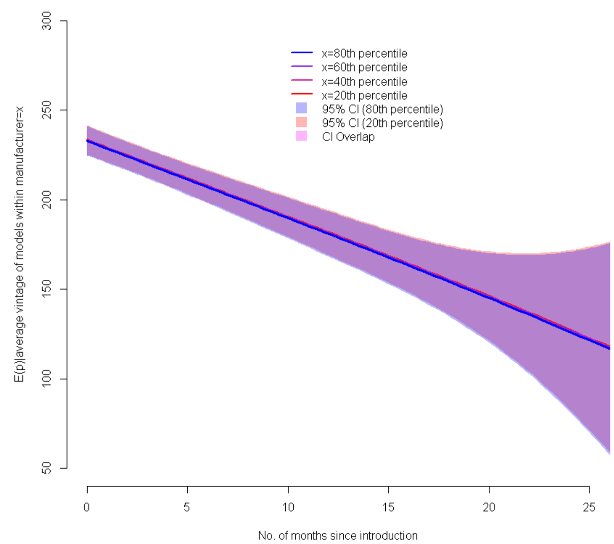
(b)Between Manufacturer Average Vintage = 40^{th} percentile



(c) Between Manufacturer Average Vintage = 60^{th} percentile



(d) Between Manufacturer Average Vintage = 80^{th} percentile

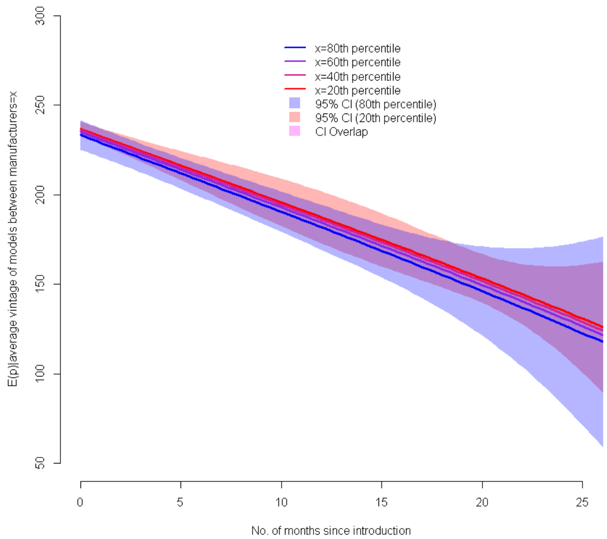


Note: The figure shows the trend in the predicted price of a representative room AC using equation 9 during its first two years. We estimate equation 9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a within-manufacturer average vintage of room AC. The 20th, 40th, 60th and 80th percentile of within-manufacturer average vintage correspond to 5.19, 8.85, 13.23, and 19.45 respectively. For the between-manufacturer average vintage, the 20th, 40th, 60th and 80th percentile correspond to 7.41, 9.08, 11.38, and 14.89, respectively.

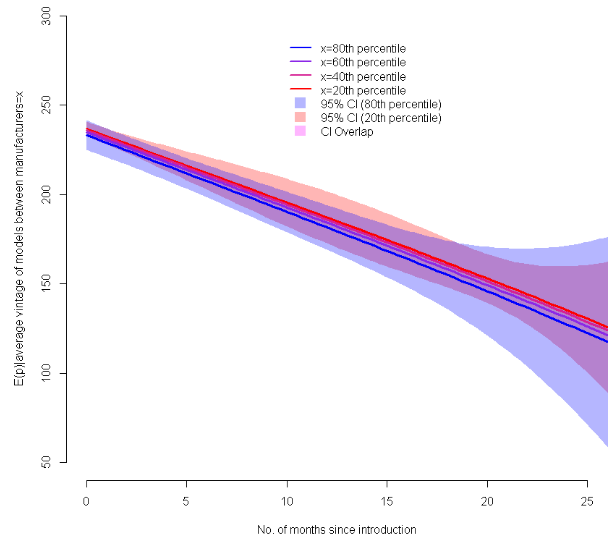
Source: The NPD Group; authors' calculation.

Figure 27: Life Cycle Pricing of Room ACs Under Different Between-Manufacturer Average Vintage

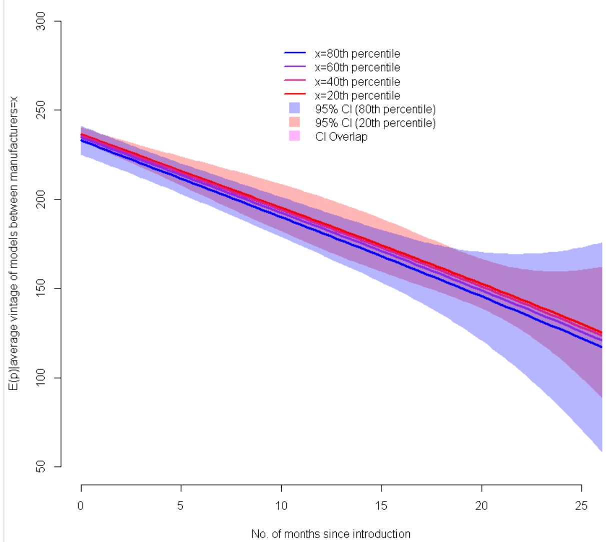
(a) Within Manufacturer Average Vintage = 20^{th} percentile



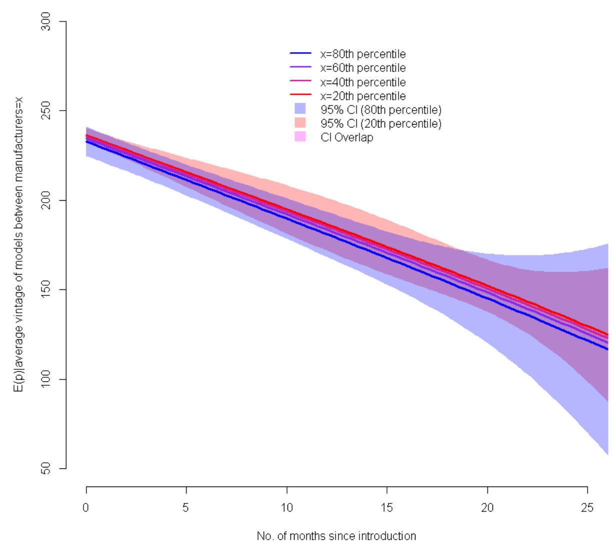
(b) Within Manufacturer Average Vintage = 40^{th} percentile



(c) Within Manufacturer Average Vintage = 60^{th} percentile



(d) Within Manufacturer Average Vintage = 80^{th} percentile



Note: The figure shows the trend in the predicted price of a representative room AC using equation 9 during its first two years. We estimate equation 9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a between-manufacturer average vintage of room AC. The 20th, 40th, 60th and 80th percentile of within-manufacturer average vintage correspond to 5.19, 8.85, 13.23, and 19.45 respectively. For the between-manufacturer average vintage, the 20th, 40th, 60th and 80th percentile correspond to 7.41, 9.08, 11.38, and 14.89, respectively.

Source: The NPD Group; authors' calculation.

G.3 Refrigerators

We use the estimates from equation 9 to predict the price trend of typical refrigerator holding average vintage of models within brands constant. Figure 16 plots this predicted price across the first two years of a refrigerator in the market, holding within-brand average vintage equivalent to about 8 months (20th percentile), 12 months (40th percentile), 16 months (60th percentile) and 20 months (80th percentile), while Figure 17 plots the predicted price holding average vintage of models *between brands* constant at about 10 months (20th percentile), 13 months (40th percentile), 15 months (60th percentile), and 19 months (80th percentile).

We also predict the price trend of a typical washer at different average vintage within the same manufacturer and between manufacturers. Figure 18 shows the predicted price of a typical refrigerator, holding average vintage of models within the same manufacturer constant at about 8 months (20th percentile), 12 months (40th percentile), 16 months (60th percentile) and 20 months (80 percentile). Figure 19 plots the predicted price at average vintage equivalent to 9 months (20th percentile), 13 months (40th percentile), 16 months (60th percentile) and 19 months (80 percentile).

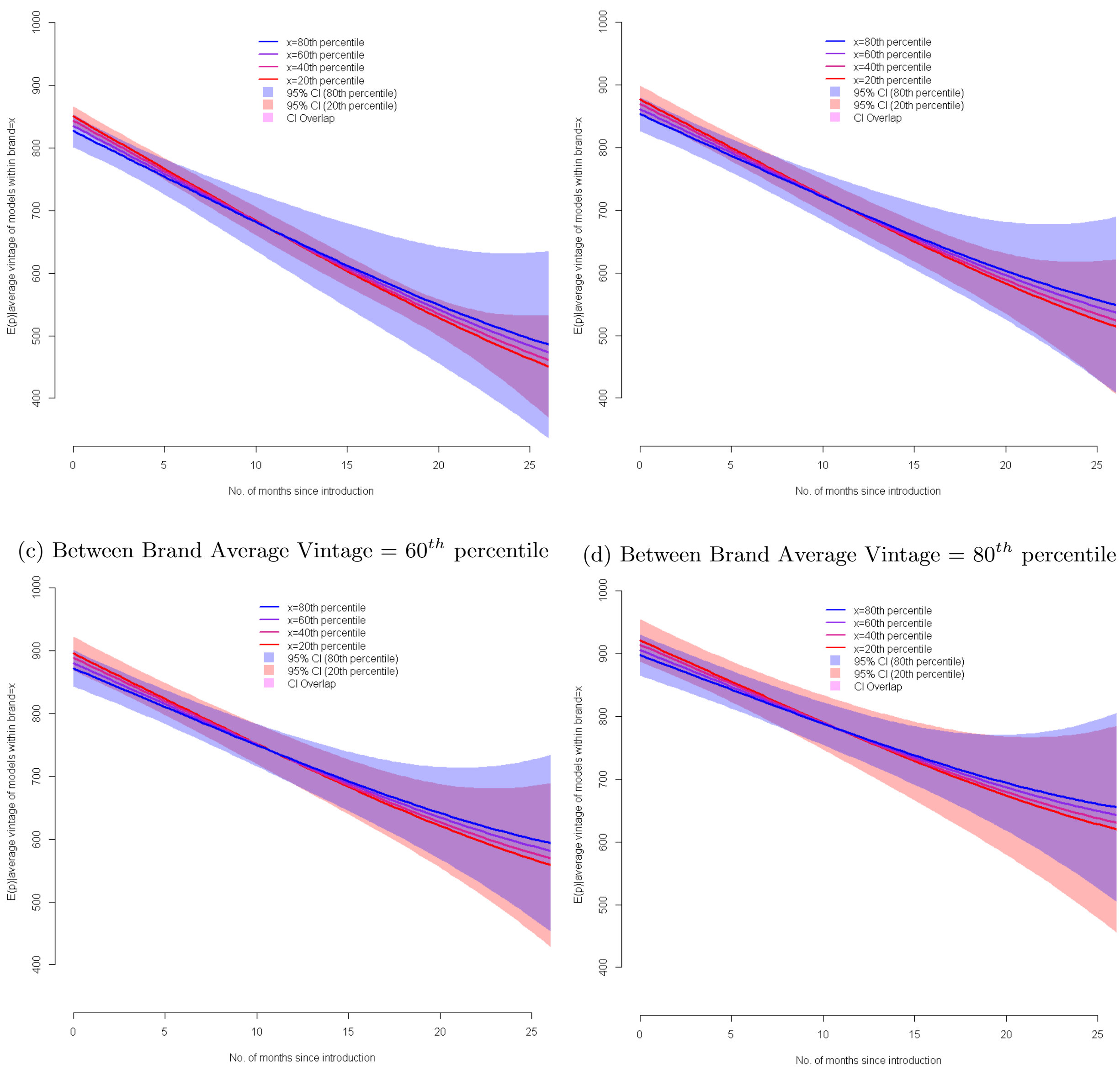
Figure 28: Life Cycle Pricing of Refrigerators Under Different Within-Brand Average Vintage

(a) Between Brand Average Vintage = 20^{th} percentile

(b)Between Brand Average Vintage = 40^{th} percentile

(c) Between Brand Average Vintage = 60^{th} percentile

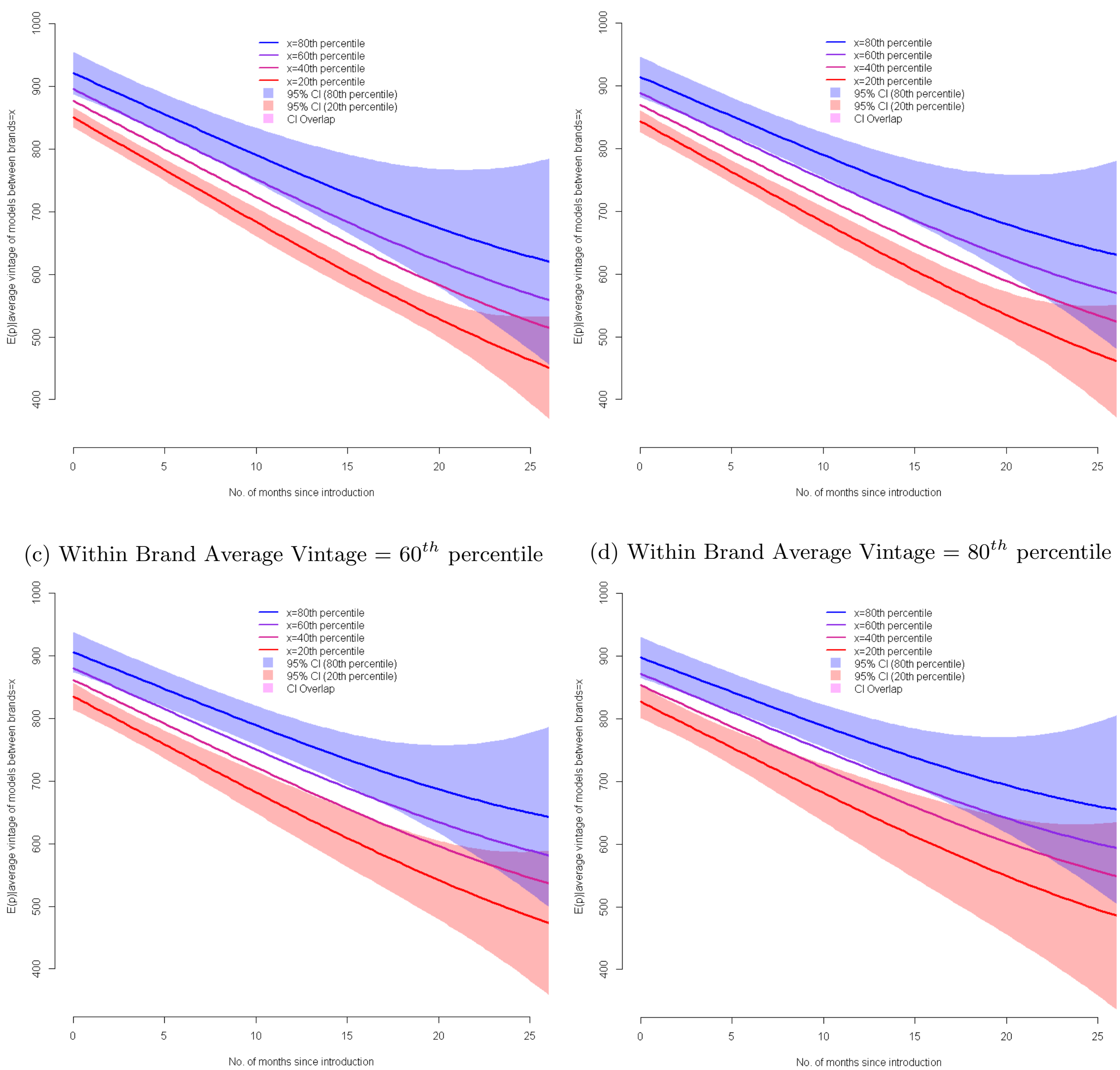
(d) Between Brand Average Vintage = 80^{th} percentile



Note: The figure shows the trend in the predicted price of a representative refrigerators using equation 9 during its first two years. We estimate equation 9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a within-brand average vintage of refrigerators. The 20th, 40th, 60th and 80th percentile of within-brand average vintage correspond to 8.23, 11.67, 15.86, and 19.98 respectively. For the between-brand average vintage, the 20th, 40th, 60th and 80th percentile correspond to 9.52, 12.93, 15.34, and 18.67, respectively.

Source: The NPD Group; authors' calculation.

Figure 29: Life Cycle Pricing of Refrigerators Under Different Between-Brand Average Vintage



(a) Within Brand Average Vintage = 20^{th} percentile

(b)Within Brand Average Vintage = 40^{th} percentile

(c) Within Brand Average Vintage = 60^{th} percentile

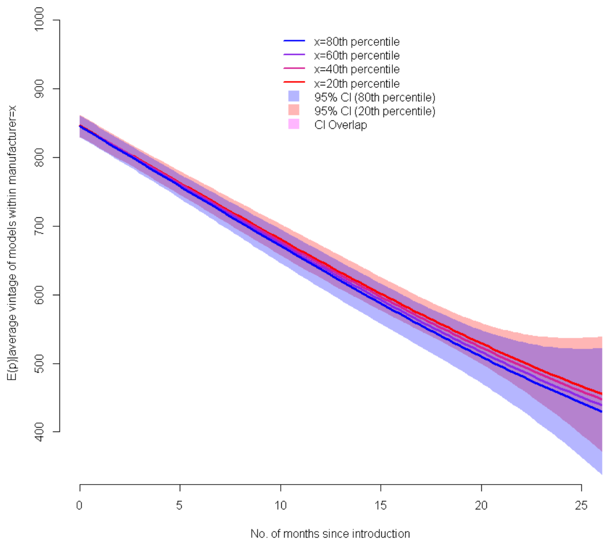
(d) Within Brand Average Vintage = 80^{th} percentile

Note: The figure shows the trend in the predicted price of a representative refrigerators using equation 9 during its first two years. We estimate equation 9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a between-brand average vintage of refrigerators. The 20th, 40th, 60th and 80th percentile of within-brand average vintage correspond to 8.23, 11.67, 15.86, and 19.98 respectively. For the between-brand average vintage, the 20th, 40th, 60th and 80th percentile correspond to 9.52, 12.93, 15.34, and 18.67, respectively.

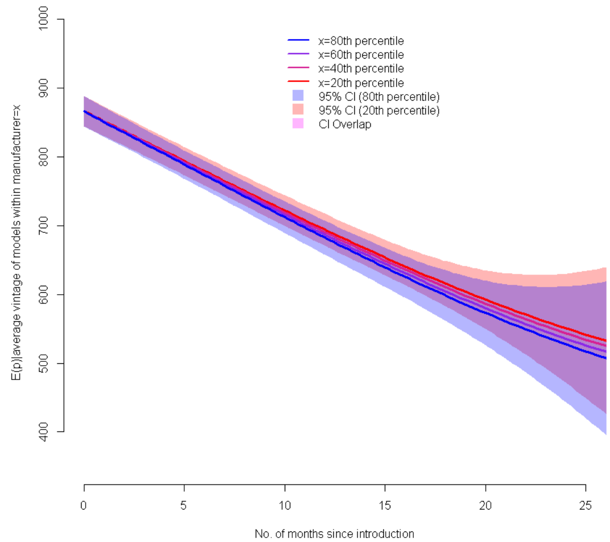
Source: The NPD Group; authors' calculation.

Figure 30: Life Cycle Pricing of Refrigerators Under Different Within-Manufacturer Average Vintage

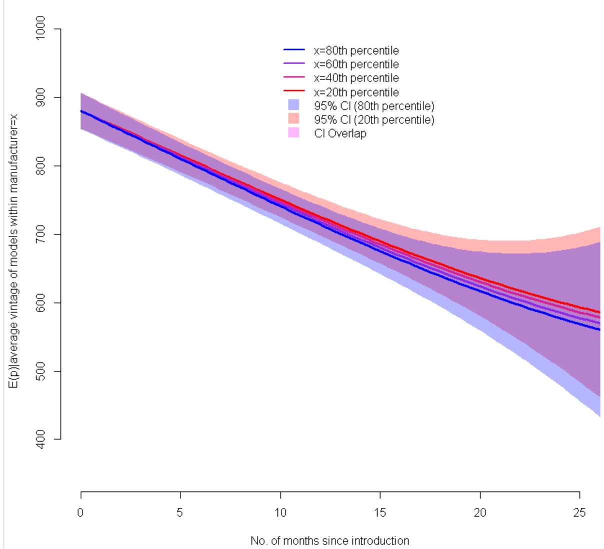
(a) Between Manufacturer Average Vintage = 20^{th} percentile



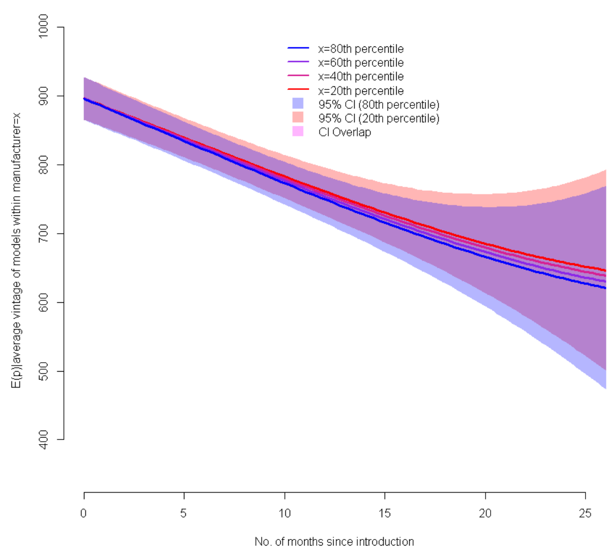
(b)Between Manufacturer Average Vintage = 40^{th} percentile



(c) Between Manufacturer Average Vintage = 60^{th} percentile



(d) Between Manufacturer Average Vintage = 80^{th} percentile

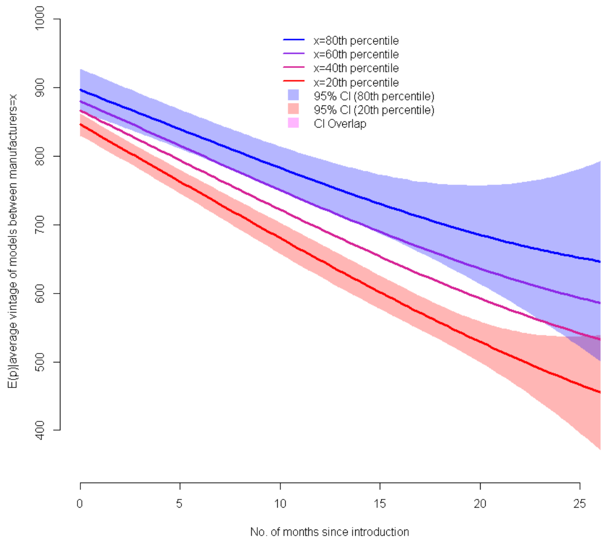


Note: The figure shows the trend in the predicted price of a representative refrigerators using equation 9 during its first two years. We estimate equation 9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a within-manufacturer average vintage of refrigerators. The 20th, 40th, 60th and 80th percentile of within-manufacturer average vintage correspond to 7.91, 11.56, 15.67, and 19.95, respectively. For the between-manufacturer average vintage, the 20th, 40th, 60th and 80th percentile correspond to 9.43, 13.13, 15.68, and 18.56, respectively.

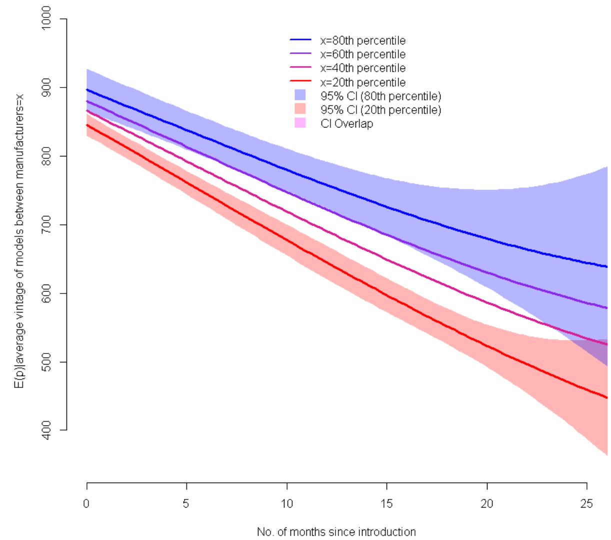
Source: The NPD Group; authors' calculation.

Figure 31: Life Cycle Pricing of Refrigerators Under Different Between-Manufacturer Average Vintage

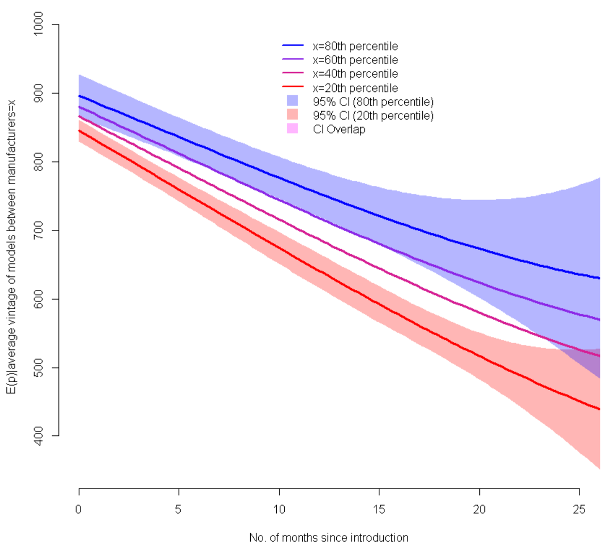
(a) Within Manufacturer Average Vintage = 20^{th} percentile



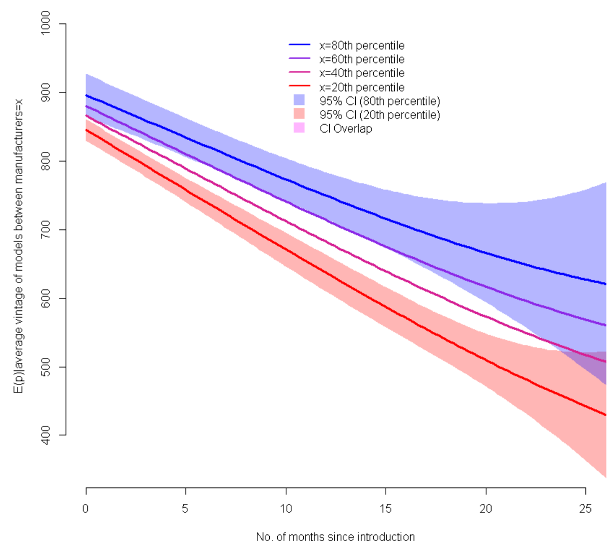
(b) Within Manufacturer Average Vintage = 40^{th} percentile



(c) Within Manufacturer Average Vintage = 60^{th} percentile



(d) Within Manufacturer Average Vintage = 80^{th} percentile



Note: The figure shows the trend in the predicted price of a representative refrigerators using equation 9 during its first two years. We estimate equation 9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a between-manufacturer average vintage of refrigerators. The 20th, 40th, 60th and 80th percentile of within-manufacturer average vintage correspond to 7.91, 11.56, 15.67, and 19.95, respectively. For the between-manufacturer average vintage, the 20th, 40th, 60th and 80th percentile correspond to 9.43, 13.13, 15.68, and 18.56, respectively.

Source: The NPD Group; authors' calculation.