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Do Energy Efficiency Standards Hurt Consumers? Evidence from Household Appliance Sales

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Abstract

Since 1987, the Department of Energy has set minimum energy efficiency standards for household appliances. Although the review process considers engineering-based accounting of costs and benefits associated with standards, economists have questioned whether these policies hurt consumers by increasing prices and limiting the scope and nature of product attributes, thereby reducing consumers' perceptions of product quality. To evaluate whether standard changes affect prices and quality, we develop a constant-quality price index using same-model price changes of appliances sold in the United States between 2001 and 2011, a period over which energy-efficiency standards changed three times for clothes washers and Energy Star thresholds were updated for refrigerators. We use this index to disentangle price changes from perceived quality changes, and develop a welfare index that accounts for both prices and quality changes over time. We then examine how price, quality and welfare changed as energy-efficiency standards became progressively more stringent. We find no indication that more stringent standards increased prices or reduced product quality. Instead, we find prices declined while quality and consumer welfare increased, especially around times when more stringent energy efficiency standards were enforced. Similar price and quality patterns emerge for refrigerators which had only Energy Star® policy changes. We conclude that standards have had at worst a negligible effect on consumer welfare, or at best lowered prices and improved quality for both washers and refrigerators, and perhaps other appliances. Further analysis suggests that standards induce innovation, but have little or no influence on inter-manufacturer competition.

JEL-Classification: D12, H23, L68, Q48

Keywords: Energy Efficiency Standards, Imperfect Competition, Price Indices

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1 Introduction

How do energy efficiency standards influence consumer welfare? With perfectly competitive markets and rational consumers, the standard economic model implies that standards make regulated durable goods more expensive or of lower perceived quality. Excluding possible external benefits from reduced pollution externalities, this would imply harm to consumers. In reality, however, markets are imperfect and consumers may choose poorly, especially with regard to product attributes with intangible future benefits, like energy efficiency. As a result, it is difficult to determine how standards ultimately influence consumer welfare, even in the absence of external benefits.

From a regulatory perspective, it is important to consider the consumer welfare implications of standards, for these are typically obscured in engineering-based estimates of costs and benefits. And though standards are not typically advocated by economists who tend to favor pricing of externalities, standards for vehicle, building and appliance efficiencies are thought to be more politically feasible than Pigouv taxes or cap-and-trade, which likely explains their prominence since the oil embargo and associated price spikes in the 1970s. In recent years, the Obama administration has pushed to make some of these standards considerably more stringent, presumably because stricter standards can be implemented under existing law, making it a feasible means of reducing greenhouse gas (GHG) emissions and other pollutants.

Many see energy efficiency as perhaps the lowest-cost way to reduce greenhouse gas emissions. 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*. LED lightbulbs, more fuel-efficient car engines, 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 as though, to a significant extent, reducing pollution and slowing climate change is a free lunch. The implicit cost not accounted for in these studies pertains to intangible product characteristics that consumers may value, but that engineering-based benefit-cost estimates cannot account.

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. The conundrum over consumers' apparent excess discounting of future energy savings dates back to early hedonic modeling (Hausman, 1979) and consumer choice studies that relate purchase decisions to product prices, energy efficiency, and other product attributes (Train, 1985). The phenomenon has been called the *energy paradox* (Jaffe and Stavins, 1994b) or the *energy efficiency gap* (Jaffe and Stavins, 1994a). Economists typically explain this phenomenon by pointing to information problems, bounded-rational behavior and/or internalities. While not all scholars are convinced that the energy efficiency gap is large or important (see, for example, Hassett and Metcalf, 1993; Allcott and Greenstone, 2012; Allcott and Wozny, 2014; Busse et al., 2013; Grigolon et al., 2014; Sallee et al., 2010), other recent studies indicate that the gap still exists and is real (Gillingham and Palmer, 2014).

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 pertain to the consequences of the standards themselves, 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, as well as broader quality and welfare effects, remain unclear.

In this study, we follow this later literature, evaluating how more stringent energy efficiency standards affect price and quality of major appliances using monthly panel, point-of sale data for models sold in the US between 2001 and 2011. We particularly exploit the relatively frequent changes in the minimum energy efficiency standard that uniquely occurred in the clothes washer market within the sample period. We also consider changes the Energy Star® thresholds for refrigerators. We also explore pricing policies applied to room air conditioners (ACs), and clothes dryers to evaluate the uniqueness of clothes washers in terms of their response to policy changes. The timing of policy changes differed somewhat across these appliances, which our empirical approach leverages. 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 formulating a Constant Quality Price Index (CQPI). Given unobserved heterogeneity of models sold over time for a particular appliance, CQPI provides a more accurate measure of price changes by considering only continuing models that were sold across multiple periods. Given an index for constant-quality prices, and assuming prices increase monotonically with quality *within* a time period, 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 local (between-period) 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.

We find no strong evidence to suggest that more stringent energy efficiency standards hurt consumers by increasing price or lowering quality. Rather, we find evidence that price declines and quality improvements accelerate with stricter standards, which unambiguously improves consumer welfare, excluding external pollution-related benefits.[1] Finally, we show evidence that policy-induced changes in price, quality and welfare are connected to entry and exit of models. Specifically, we find that price changes are more closely connected to own-manufacturer product introductions (cannibalism) as opposed to entry and exit of models by competing manufacturers, findings that suggest an innovation channel rather than a competition channel for price and quality improvements.

2 Energy Efficiency Standards

Appliances covered in this study—clothes washers and dryers, refrigerators and room ACs—are among those to either ME and ES standards. ME standards began 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 legislations, 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. The DOE reports that approximately 60 categories of appliances and equipment representing about 90 percent of household energy use are covered under ME standards.

In order to ensure the implementation of standards for covered appliance and equipment, the DOE also publishes certification, compliance and enforcement regulation for these products. These regulations include prescribed test procedures to establish certified energy efficiency ratings, as well as certification reports to DOE. Compliance to the standards is tied with the regulated appliance's manufacturing date or the date the appliance was imported for sale in the US. This implies that appliances manufactured or imported before the effective date of a new ME standard can still be sold in the US market.

Although DOE has the authority to impose regulations governing energy efficiency for many categories of appliances and equipment used in homes, businesses and other applications, each proposed rule must undergo a roughly three-year process of review, including a thorough consideration

[1] Houde and Spurlock (2015) used revealed preference approach that allowed them to calculate a price-adjusted quality index. Surprisingly, our simple and transparent methodology generates similar results indicating that our findings are robust to different empirical approaches.

of impacts to consumers and businesses (http://energy.gov/eere/buildings/process-rule). Evaluation of benefits and costs typically involve engineering-based estimates, which consider the cost of specific energy-saving technologies that can be used to satisfy proposed standards as well the discounted value of energy-related savings. A common complaint is that these explicit costs and benefits do not account for intangible benefits and costs connected to the way consumers perceive and value altered product characteristics. More energy efficient appliances may not perform as well or as desired as the less efficient appliances. By their nature, such benefits and costs are difficult to ascertain and likely impossible to evaluate before proposed standards have been implemented. In this paper we therefore develop methods to evaluate the *ex-post* net benefits of intangible consumer-related welfare impacts.

Aside from DOE's ME standards, the US government also implements the ES program. ES is a voluntary program that identifies and promotes energy efficiency through labeling of products that meet energy requirements set forth by the Environmental Protection Agency (EPA). Unlike DOE that periodically revise the federal minimum energy efficiency thresholds, EPA generally considers specification when ES certified products in a particular category reaches 50 percent or higher. Thus, the period of ES specification revision in a particular product category may not necessarily coincide with the revision of the federal minimum energy efficiency standards, although the latter also weighs into the decision to revise ES specification.

Interestingly, the timing of changes in ME and ES standards differ across major appliances covered in this study, which our empirical strategy leverages on. Clothes washers underwent major changes in both ME and ES standards in 2001, 2004, and 2011 (Table 1). The ME standard for refrigerators was revised in 2001, and ES thresholds were revised in 2001, 2004 and 2008. Finally, none of the ME and ES standards changed for clothes dryers and room ACs between 2001 and 2011.

3 Price, Quality and Welfare Measures

This study uses point-of-sale data on major appliances sold in the US to track how price and quality of the product and consumer welfare changes as more stringent energy efficiency standards are implemented. This section describes the development of constant-quality price and quality indices, as well as a welfare measure that combines price and quality changes.

Table 1: US Energy Efficiency Standards for Residential Clothes Washers and Refrigerators, 2001-2011.

Appliance	Year Effective	Federal Minimum Standard	Energy Star Standard
Clothes Washers	2001	-	MEF $\geq$ 1.26
	2004	MEF $\geq$ 1.04	MEF$\geq$ 1.42
	2007	MEF $\geq$ 1.26	MEF $\geq$1.72; WF $\leq$ 8.0
	2009	-	MEF $\geq$ 1.8; WF $\leq$ 7.5
	2011	MEF$\geq$1.26; WF $\leq$ 9.5	MEF $\geq$ 2.0; WF $\leq$ 6.0
Refrigerators	2001	30% more efficient than the 1993 standard (51% better than the 1990 standard)	10% more efficient than the 2001 standard (56% better than the 1990 standard)
	2004		15% more efficient than the 2001 standard (58% better than the 1990 standard)
	2008		20% more efficient than the 2001 standard (61% better than the 1990 standard)

Standards for washers are set based on the Modified Energy Factor (MEF), the Energy Factor (EF) and the Water Factor (WF). 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 type of clothes washers and refrigerators.

Source: Department of Energy

3.A Point-of-Sale Data on Appliances

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.[2] On the average, our data represents about 32% of the total shipments of clothes washers in the US in 2002-2011, while dryers, refrigerators and room ACs account for 32%, 35% and 25%, respectively.[3]

The data contain monthly total revenue and total quantity sold by individual model number from January 2001 to December 2011.[4] We calculate 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 models of appliances, but not mail-in rebates. To check how our price variable represents the actual selling price, we randomly selected 30 models of clothes

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

[3]A detailed discussion on the share of appliances in our sample to total US market and total shipments is found in Appendix A.

[4]Our model identification is based on brand model number, which includes brand name and detailed product attributes including colors. This is distinct from SKU number, which are codes only relevant to stores using it to manage inventory.

washers. We verified the manufacturer's suggested retail price (MSRP) of these models online and find that our price variable is 20 percent less on average, which seems reasonable given the time since NPD collected the data and the inclusion of in-store discounts.

We drop observations with prices falling below \$100 for clothes washers and refrigerators, and \$50 for room ACs, as these observations are outliers and appear unrealistic. Remaining models comprise more than 99 percent of total revenue. About 35 percent of the observations for sampled clothes washers have masked model numbers to preserve the anonymity of NPD Group's partner retailers. Refrigerators and room ACs have 40 and 70 percent observations with masked model numbers, respectively. 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 (reported in Appendix H.) Summary statistics are reported in Table 2.

Table 2: Summary Statistics

	Washer		Refrigerator		Room Airconditioner	
	Baseline	No Masked	Baseline	No Masked	Baseline	No Masked
	(1)	(2)	(1)	(2)	(1)	(2)
Price (\$)	650.55	700.09	1,378.75	1,464.47	332.53	337.18
	(355.92)	(348.89)	(1,383.51)	(1,355.75)	(240.27)	(215.76)
Sales (units)	744.00	872.30	199.61	203.68	590.72	757.67
	(1,908.47)	(2,007.55)	(736.51)	(617.18)	(3,264.15)	(3,025.81)
Revenue ('000\$)	382.40	481.45	143.15	167.16	119.11	147.71
	(966.37)	(111.02)	(451.36)	(468.18)	(581.32)	(420.69)
No. of models	2,733	1,245	15,188	6,137	3,134	878
Observations	38,504	24,838	181,513	103,501	33,290	10,477

The table shows the monthly average price, sales and revenues generated between 2001 and 2011 for the sampled appliances for each of the dataset: (1) *Baseline* treats all model numbers (including masked) as unique models, and (2) *No Masked* drops the masked models. Standard deviations are in parentheses. Observations with prices falling below \$100 for washers, dryers, and refrigerators, and \$50 for room AC were dropped as these observations are outliers and appear to be unrealistic. Prices are in December 2011 US\$.

Source: The NPD Group

3.B Disentangling Price and Quality

Panel (a) of Figure 1 shows the average price weighted by sales for clothes washers, refrigerators and room room air conditioners for the available data between 2002 and 2011. For clothes washers and room air conditioners, the trend is generally flat. For refrigerators, the trend is upward from 2002 through 2007 and then tend to flatten up to 2011. Significant drops around January 2004 and

January 2007 changes in efficiency standards are evident.

Changes in average price likely include changes in the mix of models sold as well as quality changes, as models enter and exit the marketplace and the distribution of buyers fluctuates. Changes in mix and overall quality may be driven 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 an appliance change over time, we develop 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 same-model prices. Specifically, denote p_{it} as the price in period t of a particular model i and q_{it} as the associated quantity sold. For all models sold in *both* t and $t-1$, we calculate:

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

where

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

and

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

Although the set of models used in calculating the change in CQPI generally differs across time periods, the set is fixed for any given change, and thereby holds quality constant.

One concern about the CQPI is that model weights depend on quantity sold and are thus endogenous to price. Consumers may substitute toward products with larger price declines, causing a bias in the average change. 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, which indicates this is in fact a trivial concern. Appendix 11 reports these alternative constructions.

Another concern about the CQPI is that price changes across product vintage (see Appendix B). Clothes washers and room air conditioners have lower prices as the product ages, typically declining by about 10 percent after a year. For refrigerators, average price drops by about 20 percent one month after introduction and slightly increases thereafter. 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. As we show below, 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 regression model is:

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

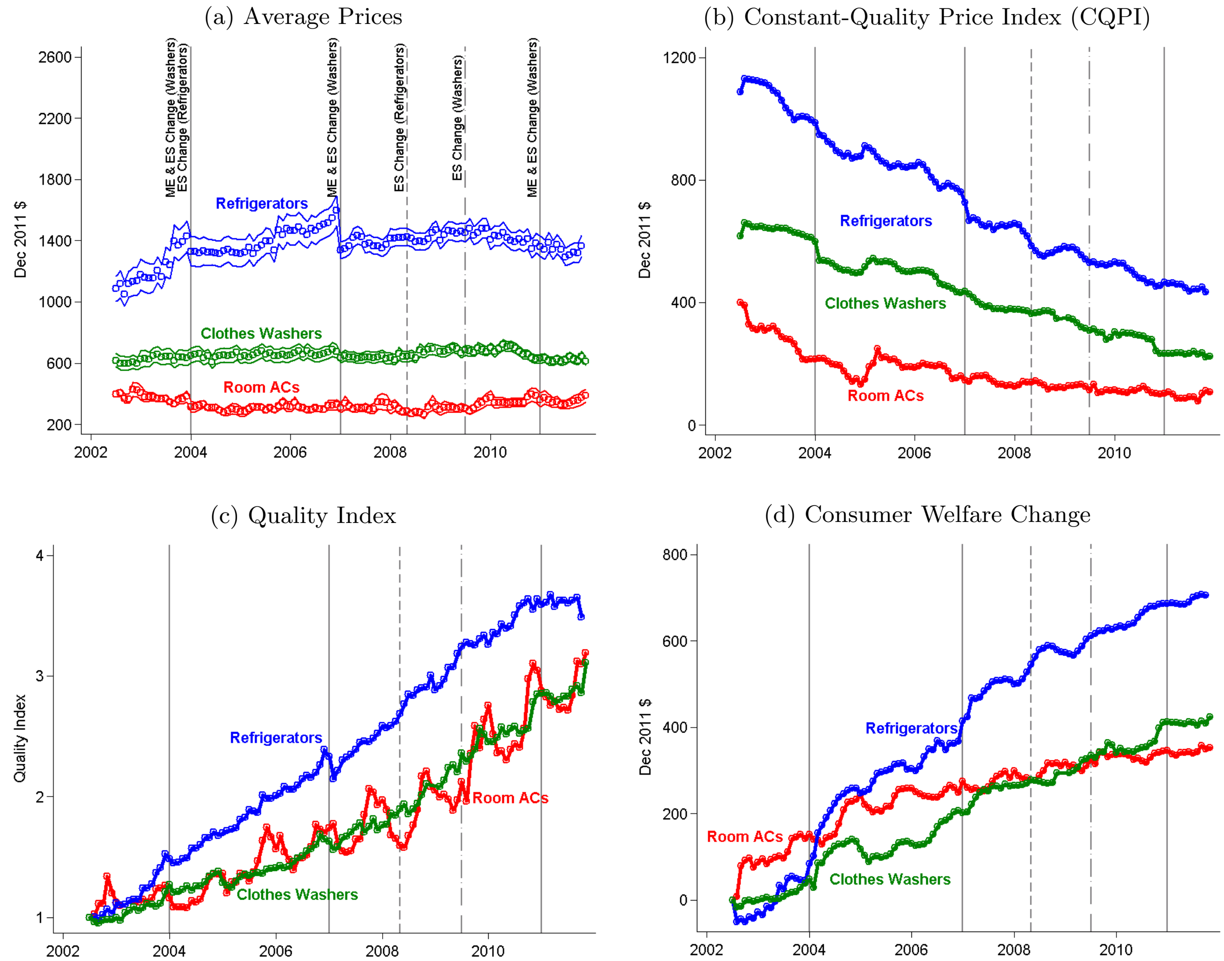
where p_{it} denotes the price of model i at time t, α_i is a model fixed effect, v_k is vintage fixed effect for vintages $k \in \{2, ..99\}$ representing periods since first introduction, γ_t is a time period fixed effect, and ε_{it} is the error. Because the CQPI excludes entering and exiting models, 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.

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, adjusting for vintage effects as described above. Based on the CQPI and quality index, we develop a consumer welfare indicator associated with changes in prices (holding quality constant) and quality of appliances in a particular period.

3.C Consumer Welfare

Consumer welfare impacts are influenced by both price and quality changes. In this section we develop a simple framework that estimates the total welfare impact of these changes, assuming the *quantity* of appliances sold is unaffected by price and quality changes. In other words, we evaluate welfare effects of the quality decision. Higher quality appliances are more expensive and the price of quality is relative. Income not spent on appliance quality can be spent on other goods and services. As appliance prices fall, the budget constraint pivots out, allowing the consumer to buy a higher quality appliance while spending less (Figure 2). The figure shows standard constrained consumer choice, with appliance quality on the horizontal axis and the numeraire (real dollars) on the vertical axis. As appliance prices fall, the consumer's choice moves from point A to point B on

Figure 1: Market Average Price, CQPI, Quality and Consumer Welfare Trend for Clothes Washers, Refrigerators, and Room ACs, 2002-2011.



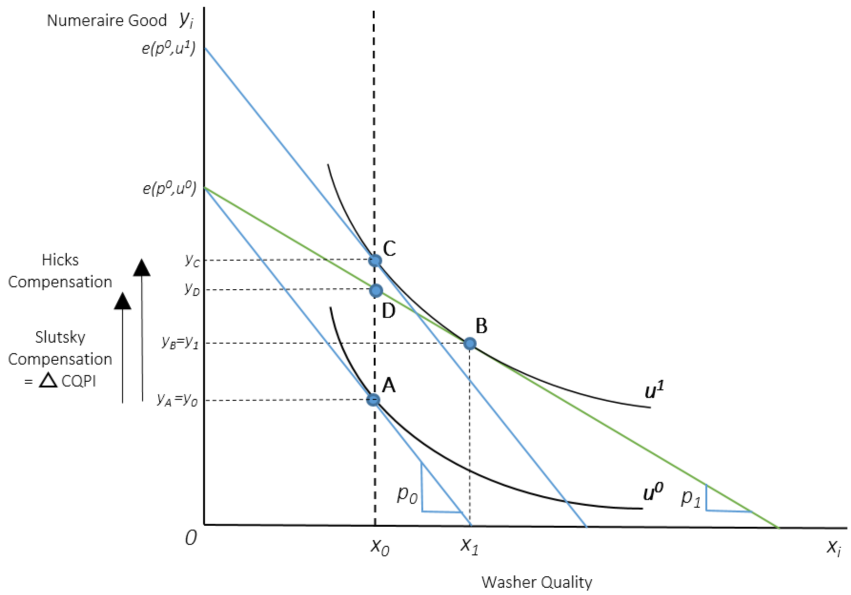
Notes: Panel (a) show sales-weighted average prices and 95 percent confidence bands for each appliance across time; panel (b) shows the constant-quality price index (CQPI), calculated from the average of same-model price change, adjusted for vintage effects; panel (c) shows the quality index, constructed as the ratio of average price over constant-quality price, and panel (d) shows the calculated consumer welfare change as discussed in section 3.C. The solid red vertical lines represent the effective date of simultaneous policy changes in the federal minimum energy efficiency standard and Energy Star certification threshold, while the dashed line is for the Energy Star threshold change that took effect in July 2009, all for clothes washers. Refrigerators had changes in Energy Star certification thresholds in January 2004 and in May 2008 (represented by the dashed dotted vertical line). All prices are in December 2011 US dollars.

Source: Monthly sales and revenues of clothes washers sold in the US between 2001-2011 (The NPD Group) and authors' calculations.

the graph.

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

Figure 2: WELFARE IMPLICATIONS OF A PRICE FALL OF CLOTHES APPLIANCES



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, an assumption that can be justified on two counts: (1) appliance purchases account for a small share of representative buyer's lifetime income, while the changes in appliance prices are a couple orders of magnitude smaller, and (2) we recalibrate utility between every two periods, such that small income effects, if present, will not accumulate. Moreover, the quasi-linear utility assumption underestimates Hicksian compensation when price falls, which makes our consumer welfare estimate conservative. A quadratic approximation should provide a reasonably accurate estimate an arbitrary utility function while allowing for a simple and tractable measure.

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

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,

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

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

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 demand and Hicksian 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 appliance 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 appliances in the initial period, which we denote $\bar{w}_0$. As appliance 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.[5] Note that if there were no substitution toward quality then the Slutsky compensation—equal to $-\Delta$CQPI—would equal the welfare change. We therefore call the difference between ΔW and ΔCQPI the Quality Substitution Effect (QSE).

Panels b and c of Figure 1 summarizes the trend in the CQPI and the cumulative changes in consumer welfare between 2002 and 2011 for clothes washers, refrigerators and room ACs. For washing machine, the CQPI fell by $464.00 over time, generating an estimated consumer welfare gain of $474.25; 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. This pattern also occurs for refrigerators which had ES policy changes in 2004 and 2008.

4 Effects of Standard Changes on Prices, Quality and Welfare

The empirical strategy leverages on the fact that minimum efficiency and Energy Star standards changed at different times for different appliances. Thus, appliances not experiencing a change in standards serve as a control for appliances that do have standard changes. We estimate the effect that standards had on price, quality and consumer welfare measures using differences (pre/post) and difference-in-differences (DD) comparisons, which requires estimating equation 7. The dependent variable, y_{it}, is the percentage change in CQPI or quality index, or level change in welfare for a specific appliance i. ME_{it} and ES_{it} are dummy variables which turn on at the time new federal ME and ES standards, respectively, are assumed to have affected the outcome variable. ε_{it} is the usual error term. The coefficients of interest are β_1 and β_2, which account for policy-affected periods of the treatment.

$$y_{it} = \beta_0 + \beta_1 ME_{it} + \beta_2 ES_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \tag{7}$$

[5] In Appendix C we show how a few specific product attributes relate to the quality index.

4.A Estimates Based on Differences

Table 3 summarizes the average change in the CQPI, quality index and welfare estimates for washers with the 2004, 2007 and 2011 simultaneous ME and ES policy changes, as well as the 2009 ES policy change; for refrigerators with 2004 and 2008 policy changes; and room ACs with constant ME and ES standards within the sample period.

Table 3: Average Change in CQPI, Quality Index and Welfare
Washers vs. Refrigerators vs. Room AC, 2002-2011.

Period	Clothes Washers			Refrigerators			Room AC		
	CQPI	Quality	Welfare	CQPI	Quality	Welfare	CQPI	Quality	Welfare
Pre-2004	0.388	1.139	0.291	-0.246	1.322	3.113	-1.803	1.336	9.178
2004 ME & ES Policy	**-1.659**	**1.390**	**9.173**	**-1.441**	**2.712**	**14.365**	-0.981	0.181	3.830
Post-2004 Policy	0.256	0.910	-1.236	-0.874	1.269	7.405	-1.327	1.578	4.860
Pre-2007 Policy	-0.827	0.673	4.443	-0.551	1.177	4.333	-0.955	1.029	2.714
2007 ME & ES Policy	**-1.845**	**1.984**	**8.665**	-1.600	1.024	11.296	-0.174	0.460	1.148
2008 ES Policy	-0.578	0.890	2.288	**-0.923**	**1.200**	**5.172**	-0.959	1.496	2.192
2009 ES Policy	**-1.752**	**1.400**	**5.797**	-0.876	0.882	4.359	-0.882	2.161	2.161
2011 ME & ES Policy	**-1.899**	**1.214**	**5.199**	-0.710	0.529	3.003	-0.722	1.203	1.203

Change in consumer welfare is measured as ΔConsumer Surplus, while changes in CQP and Quality Index are in percentage terms. 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. Bold figures reflect periods where the appliance underwent a policy change. Refrigerators only had ES policy changes within the sample period.

Source: Monthly sales and revenues of clothes washers, refrigerators and room ACs sold in the US between 2002-2011 (The NPD Group); CQPI, quality index and consumer welfare measure (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 (because standards ban the manufacture, not the sale, of appliances below the efficiency threshold), 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 Appendix E, we report results when the window includes only three months. 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 declines in CQPI and increases in quality and welfare are larger around policy changes relative to previous and succeeding periods.[6] For example, the average

[6]Note that acceleration in quality increases around policy changes is *not* due to vintage effects (e.g., a large

monthly drop in the CQPI for clothes washers around the 2004 ME and ES policy change was about 1.3 and 1.54 percentage points more than the pre- and post-policy periods, respectively. Interestingly, average decline in CQPI are generally larger during periods of ME policy changes, even though only clothes washers underwent policy changes in ME standards. For refrigerators, average decline in monthly CQPI is larger during periods of ES policy changes, except in 2007 where average decline is significantly larger even if standards remain at the 2004 level.

4.B Estimates Based on Difference in Differences

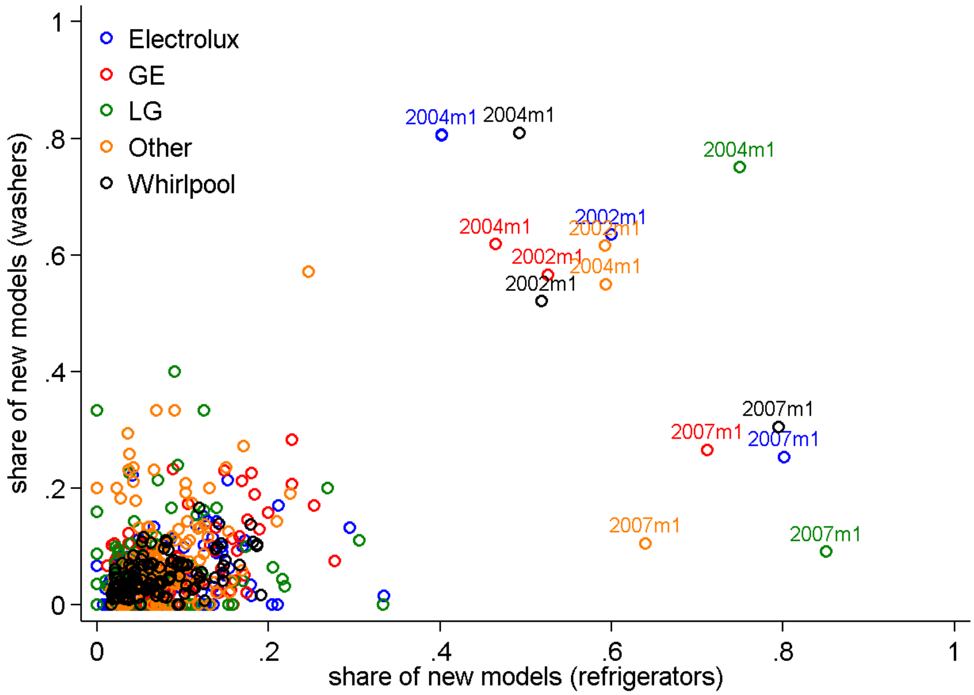
Except for rapidly declining CQPI for room ACs prior to 2004, statistics for the three appliances follow similar trends, including the significant drop around ME policy changes. Based on the data alone, it is hard to know whether the correlated effects are due to unobserved factors, like the housing boom in 2004, or because the policy change for washing machines also affected other appliances, although the sharp effects right at the policy changes in 2004, 2007 and 2011 lean against the idea of a common unobserved factor. Furthermore, it is plausible that if a manufacturer of clothes washer is compelled by the policy change to introduce new models in the market, it would be spreading its overhead fixed costs (e.g. engineering and logistics) further by upgrading other appliances, like refrigerators and room ACs, at the same time.

To examine spillover effects by comparing the timing of product introductions for clothes washers and 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 3). 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 G).

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 and room ACs as controls. 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 3. Regression results from estimating equation 7 are reported in Table 4. Columns labeled (1)-(2) include clothes washers and refrigerators and (3) includes room ACs in the sample. Columns (2) includes the intersection of month and refrigerator dummies to control for seasonality for refrigerators, and (3) adds intersection of month and room AC dummies to control for the appliance's seasonality in the variables of interest. We find evidence to suggest that constant-quality prices fall while quality and consumer welfare increase on the average as a result of the policy change. Although the estimates

introduction of new models), as these have been excluded. Instead, it comes from substitution toward higher-quality continuing models as prices generally fall.

Figure 3: Correlation in the share of new models between washers and refrigerators, 2001-2011



A list of manufacturers and their subsidiary brands are presented in Appendix F.

Source: The NPD Group.

are generally small, the estimates represent a worst-case outcome for consumers. Standards on washers and refrigerators have had at worst a negligible effect on consumer welfare, or at best lowered prices and improved quality for both washers and refrigerators.

5 Competition and Innovation

Earlier we presented evidence that prices decline with vintage. One explanation for this pattern might be that the vintage effect derives from competition, that policy-driven 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 of an appliance, regardless of vintage, the lower is average vintage, the more new, presumably higher-quality models with which it must compete. By forcing gradual exit and entry, standards may significantly alter the distribution of vintages and thereby affect innovation and competition. To investigate this hypothesis, we calculate average vintage, or average time since market introduction for the clothes washers, which had simultaneous policy changes in ME and ES standards within the sample period. We found that average vintage declines

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

Variables	Dependent Variable								
	Δ CQPI			Δ Quality			Δ Welfare		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
ME and ES	**-1.199****	**-1.206****	**-1.547****	**0.550**	**0.558**	**1.003**	**2.503**	**2.620**	**5.412****
	(0.591)	**(0.526)**	**(0.605)**	**(0.772)**	**(0.763)**	**(0.750)**	**(3.023)**	**(2.738)**	**(2.242)**
ES Only	**-0.744***	**-0.676***	**-0.759**	**0.863**	**0.853**	**0.982**	**3.623***	**3.264***	**4.342****
	(0.431)	**(0.400)**	**(0.573)**	**(0.578)**	**(0.538)**	**(0.684)**	**(1.946)**	**(1.898)**	**(1.874)**
Constant	0.520***	0.355	1.687*	-4.183***	0.325	-3.332**	-3.224***	4.237	1.295
	(0.124)	(0.370)	(0.890)	(0.176)	(0.773)	(1.641)	(0.669)	(4.056)	(5.087)
Appliance FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month x Ref	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Month x AC	No	No	Yes	No	No	Yes	No	No	Yes
R-squared	0.681	0.761	0.681	0.538	0.597	0.598	0.692	0.762	0.651
Adj. R-squared	0.338	0.446	0.456	0.041	0.066	0.316	0.361	0.448	0.406
Observations	221	221	333	221	221	333	221	221	333

ME and ES are dummy variables which turn on at the time new federal ME and ES standards, respectively, are assumed to have affected the outcome variable. 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)-(2) include clothes washers and refrigerators and (3) adds room ACs in the sample. Month x REF and Month x RAC are intersections of month and appliance dummies for refriegerators and room ACs, respectively, to account for seasonality that is evident for the appliances. Robust standard errors are in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10 percent level, respectively.

Source: Monthly sales and revenues of appliances sold in the US between 2002-2011 (The NPD Group); vintage-adjusted CQPI, quality index and consumer welfare measure (Authors' calculation).

sharply around the times of major policy changes (Figure 4).

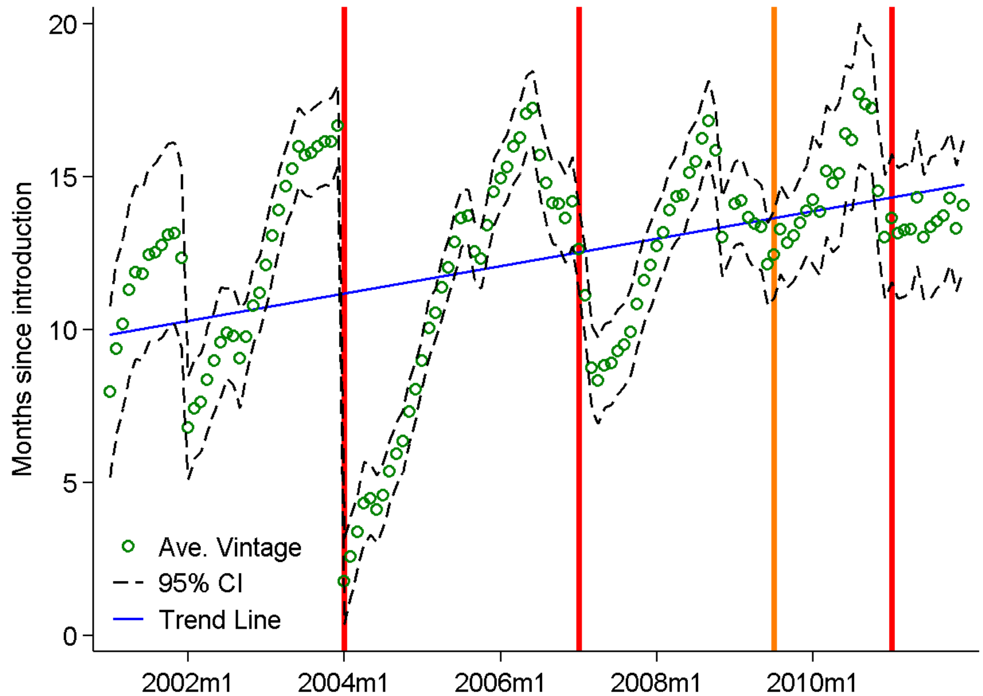
A concern with interpreting the data in Figure 4 is that a decline in average vintage may not be solely due to the regulatory changes. For example, average vintage also declines during early months of 2002, 2006 and 2008, when no policy changes occurred. These changes may be a result of a large firm's 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:

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

where p_{it} denotes the price of model i at time t, $\overline{vintage}_{-i,t}$ is the average vintage (weighted by

Figure 4: Average Vintage of Clothes Washers, 2001-2011



Vintage indicates the number of months since a product was introduced. 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 were dropped as these observations are outliers and appear to be unrealistic.

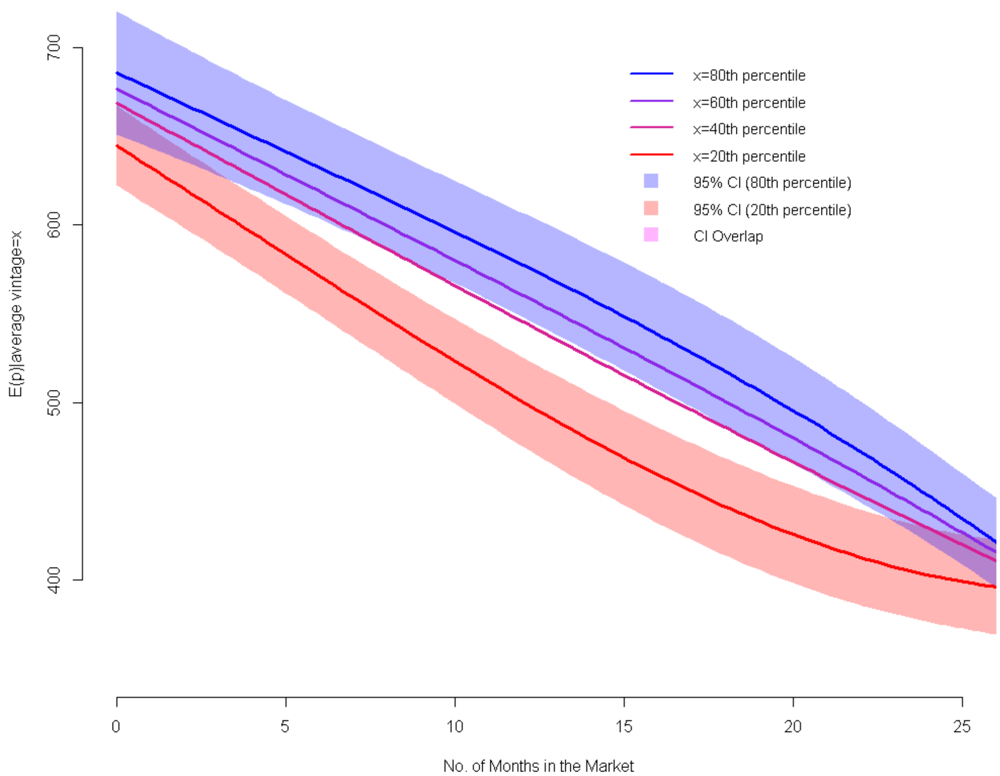
Source: The NPD Group.

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 excluded model 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.

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 5 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 5 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 (see Table 6). Significance tests are summarized in Table 5.

Figure 5: Life-Cycle Pricing of Clothes Washers Under Different Average Vintage



Each solid line represents a predicted price trend, given an average vintage of 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.

Source: Authors' calculation.

Table 5: ANALYSIS OF VARIANCE FOR (REAL) PRICE

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

The table reports F-tests for the joint significance of key explanatory variables and their interactions with the vintage (number of months since introduction) of the clothes washer in the market. The model uses restricted cubic splines with 5 knots, which results in four factors in the regression equation. 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.

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.

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.

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

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 6 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).[7] We find no statistically signifi-

[7] Appendix I plots that assume contains plots that hold between-brand average vintage at 13 months (40th per-

cant 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 6). Reducing the average vintage from 15 months to 10 months is associated with a 3% price decrease, all else the same (see Table 6).

Table 6: Regression Results: Dependent Variable - Unit Price, Clothes Washers and Dryers

	Clothes Washers		Clothes Dryers	
	(1)	(2)	(3)	(4)
β_1, average vintage within brand	2.017***		2.535***	
	(0.379)		(0.262)	
β_2, average vintage between brands	3.145***		3.580***	
	(0.630)		(0.501)	
β_1, average vintage within manufacturer		3.905***		4.657***
		(0.427)		(0.262)
β_2, average vintage between manufacturers		0.744		1.736***
		(0.462)		(0.381)
Constant	719.932***	722.204***	617.112***	612.562***
	(6.322)	(6.005)	(4.950)	(4.823)
Own Vintage Spline	yes	yes	yes	yes
Month-Fixed Effect	yes	yes	yes	yes
Model-Fixed Effect	yes	yes	yes	yes
Adj. R^2 (within group)	0.298	0.300	0.317	0.326
Observations	38,282	38,477	64,794	64,859

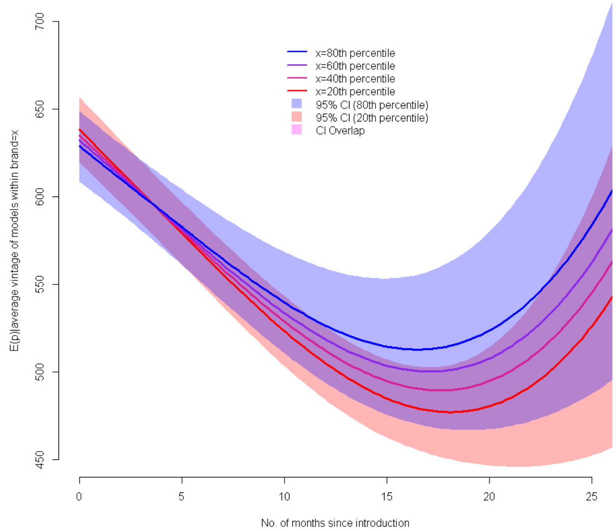
The table reports the results from estimating equation 9 without the interaction effects. Columns (1) estimates the effects of within- and between-brands average vintage, and (2) estimates the effects of within- and between-manufacturer average vintage on price. Clustered standard errors are in parentheses. We use restricted cubic splines with 5 knots in estimating the spline function of vintage. ***, **, * indicate significance at the 1, 5, and 10 percent, respectively.

Since the clothes washer market is dominated by large integrated manufacturers with several subsidiary brands, 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. Panel (c) in Figure 6 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

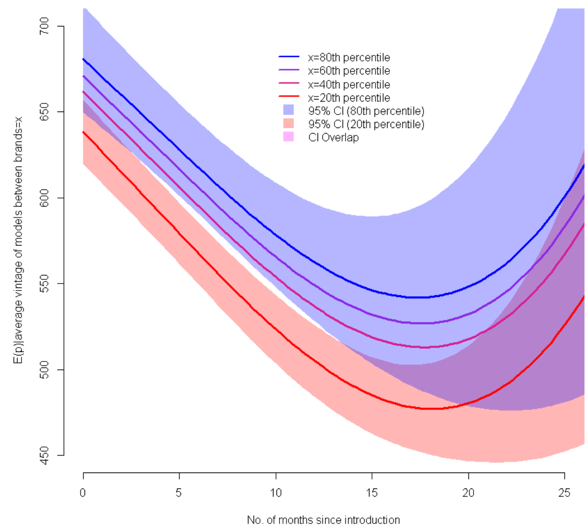
centile), 14 months (60th percentile) and 15 months (80 percentile)

Figure 6: Life Cycle Pricing of Clothes Washers

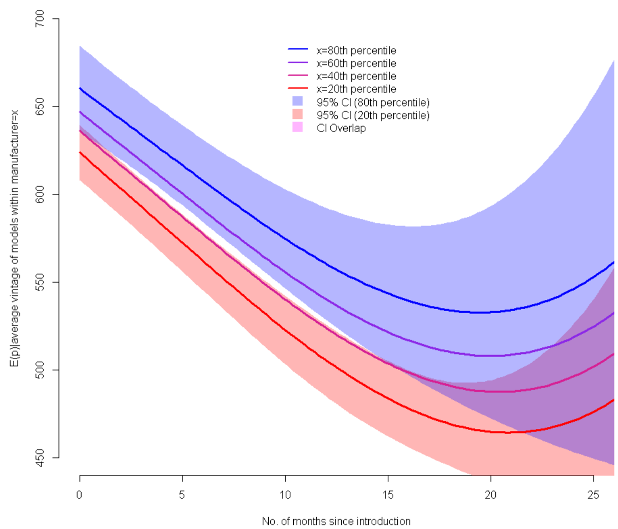
(a) Different *Within-Brand* Average Vintage



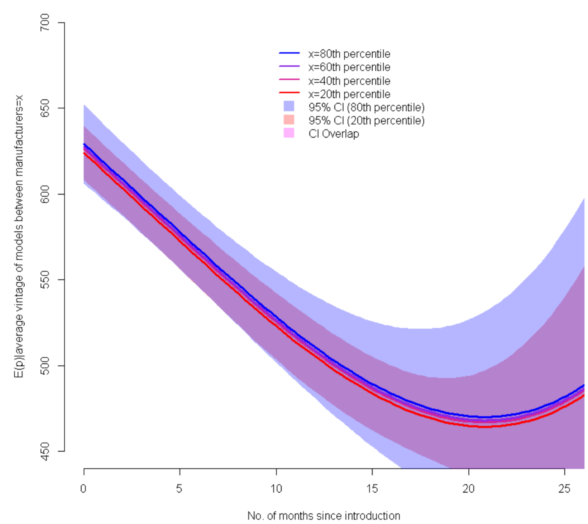
(b) Different *Between-Brands* Average Vintage



(c) Different *Within-Manufacturer* Average Vintage



(d) Different *Between-Manufacturers* Average Vintage



Each solid line represents a predicted price trend using equation 9 during its first two years, holding average vintage within- and between-brands (for panels a & b) or manufacturers (for panels c & d) constant. 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. For within-manufacturer average vintage, the 20th, 40th, 60th and 80th percentile correspond to 8.86, 11.14, 13.18, and 15.68, respectively; and 9.47, 12.53, 13.85, and 16.12, respectively, for between-manufacturers average vintage.

Source: Authors' calculation.

16 months (80 percentile).[8] The difference between 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 (Panel d).

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 ES certification change during the study period, although refrigerators had ES policy changes in 2004 and 2008. We use the estimation strategy presented in equation 9 for these appliances. Table 6 presents the regression results using equation 8 for clothes dryers and Table 7 is for refrigerators and room ACs.

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 (Table 6). 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.

6 Discussion

Contrary to some views that more stringent energy efficiency standards are costly primarily due to higher upfront costs associated with more energy efficient appliances, we find no strong evidence suggesting that implementing stricter energy efficiency policies increases prices of regulated appliances. At best, prices may actually have declined and overall quality improved as a result of energy efficiency policy changes. Overall, consumers unambiguously gain, holding other things constant.

The observed declining trend of price in section 3 can be due to several factors. For example, unit price may decline because firms are resorting to intertemporal price discrimination in order 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

[8] We repeat this prediction for different between-manufacturer average vintages in Appendix I.

Table 7: Regression Results: Dependent Variable - Unit Price, Room ACs and Refrigerators

	Room AC		Refrigerator	
	(1)	(2)	(3)	(4)
β_1, average vintage within brand	0.158		4.264***	
	(0.130)		(0.411)	
β_2, average vintage between brands	0.999***		4.429***	
	(0.202)		(0.739)	
β_1, average vintage within manufacturer		0.002		0.137
		(0.003)		(0.084)
β_2, average vintage between manufacturers		1.109***		6.829***
		(0.175)		(0.706)
Constant	403.189***	403.503***	1450.485***	1465.583***
	(3.986)	(4.021)	(8.646)	(8.253)
Own Vintage Spline	yes	yes	yes	yes
Month-Fixed Effect	yes	yes	yes	yes
Model-Fixed Effect	yes	yes	yes	yes
Adj. R-Squared (within group)	0.115	0.115	0.101	0.098
Observations	45,324	45,305	181,277	181,449

The table reports the results from estimating equation 9 without the interaction effects for room ACs and refrigerators. Columns (1) and (3) estimate the effects of within- and between-brands average vintage, while (2) and (4) 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. ***, **, * indicate significance at the 1, 5, and 10 percent level, respectively.

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. If the user value of having the appliance in a timely manner is sufficiently high, as is likely the case with clothes washers and perhaps other appliances, it's easy to see why many buyers would be unwilling to wait for price to fall or quality to rise.

Unit price may also decline as firm's costs decline over time, potentially due to learning-by-doing. As firms continue to produce appliances, productivity may increase and cost may fall through practice and continued innovation. However, 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. In section 5, we find that lower average vintage significantly declines unit price.

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.

Figure 4 illustrates how the distribution of product vintages shifts periodically, with average vintage dropping sharply right around policy changes. This trend is product vintages imply that standards may be forcing firms to force gradual entry and exit of models in the market, thus altering the distribution of vintages and affecting innovation and competition. As we have shown, for example, the simultaneous change in ME and ES for clothes washers may have induced most manufacturers to introduce new models at the same time in January 2004, which makes the effect of vintage-effect adjustment on price relatively more significant than in other periods.

We also find evidence to suggest that most and perhaps all the price declines with average vintage are associated with increased entry and exit of models that occur within the same manufacturer. This pattern is uniquely strong for clothes washers that had undergone simultaneous and relatively more frequent changes in ME and ES standards. 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 market 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 the price of an existing product (Padmanabhan and Bass, 1993).

Although policy changes appear to benefit consumers, there are important caveats. First, the welfare analysis is based on a representative consumer. In reality, however, different consumers care to varying degrees about various product characteristics, an aspect of demand that the model may not fully capture. Discrete choice models like Berry et al. (1995) and McFadden and Train (2000) can account for heterogeneity of preferences and complex monopolistically competitive market structure. However, one must impose restrictive and otherwise questionable assumptions in using these models to extract certain distributions of consumer utilities (Berry et al., 2004). Different methods exist, but require 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.

A second caveat is that while one might reasonably attribute at least some of the consumer welfare gains to changes in energy-efficiency standards, perhaps through policy-induced innovation (Ronnen, 1991), it's not clear how much of the overall decline in prices and improvement in quality would have occurred in the absence of the standard changes. To consider the effects of policy, a control is needed. This makes the establishment of counterfactuals extremely difficult due to the observed positive correlation of entry and exit of models among major appliances, which might be a result of large manufacturers' attempt to reduce overhead and logistics costs associated with introducing new appliances at different time periods. This caveat, however, only makes our estimate more conservative and can interpreted as the lower bound of the effect of the standard change.

We also note that policy changes were anticipated far in advance of implementation, and affect the manufacture of washers but not their sale. Thus, there is no reason to expect a sharp discontinuity at the time of policy change. As a result, it makes it more 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.

This study does not look into firm's welfare in analyzing the impact of stricter energy efficiency policies, largely due to data limitations. It is plausible that firms manufacturing regulated appliances might experience profit losses as they re-optimize their products and processes to meet compliance requirements (Whitefoot et al., 2013). The magnitude of these profit losses is unknown and may largely depend on how firms respond to the new policy (which may include violating the standards), making the overall welfare impact of imposing more stringent energy efficiency standards uncertain.

7 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 improve environmental quality while simultaneously addressing 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 and dynamic pricing concerns. 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 asess implicit values from consumer choices, we attempt to measure the implications of actual standard changes on market outcomes. From these outcomes we develop methods that allow us to ascertain the *ex-post* welfare implications associated with restricted product variety and changing prices, factors that heretofore have been acknowledged but difficult to assess. While standard changes provide some pre-post basis for comparison, and we construct a kind of quasi experiment using other appliances as controls, 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 clearly indicate that past standard changes did little to harm consumers and likely improved consumer welfare considerably. We find remarkable declines in constant-quality prices of appliances, 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 $474.25 per clothes washer assuming quasi-linear utility, and lower bound of $464.00 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 difficult to square these observations with an argument that efficiency standards cause a great burden to consumers. It is important to emphasize that these estimated benefits are *in addition to* external environmental benefits or benefits that may arise from correcting behavioral errors associated with possible undervaluation of energy efficiency, and perhaps quite different from those that may have been intended.

What might explain these counterintuitive effect of standards on consumer welfare? One theory is that standards make heterogeneous products more homogeneous, and thereby increase competition as theorized by Ronnen (1991). Another possibility is that standards facilitate innovation (Jaffe and Palmer, 1997). We find little evidence of increased competition as a mechanism, since entry of other-manufacturer products has little influence on own-manufacturer prices. But we find evidence supporting policy-induced innovation, wherein firms lower prices of older models as they are forced to introduce new model meeting new, stricter efficiency standards. Of course, firm profits may have decline as a result of the policy changes, an aspect of the issue we cannot address in this paper.

More generally, these findings clarify that the evaluation of energy efficiency standards pertains to much more than pollution externalities and the existence, size, and causes of the energy efficiency gap. Energy-consuming durable goods markets contain 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.

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 of 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 Market Share of Appliances Sold in the Point-of-Sale (POS) Data

This section presents the market share of the sampled major appliances sold in the US between 2002 and 2011. Estimated total revenue and total units sold for the entire US market is from the NPD Group. Total shipment for each appliance were collected from the Association of Home Appliance Manufactures (AHAM). Tables 8 and 9 show market share estimates for clothes washers and dryers, respectively. Tables 10 and 11 show market share estimates for refrigerators and room ACs, respectively.

Table 8: Market Share of Sampled Clothes Washers, 2002-2010.

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	Ave.
US Market (Total)											
Total revenues	3,186.48	3,068.00	3,270.34	4,146.03	4,251.19	4,425.06	3,979.87	3,786.15	4,231.43	3,638.10	
Total sales	7,074.15	6,566.20	7,113.55	8,554.21	8,047.12	7,963.80	7,494.35	7,074.19	7,994.68	7,009.73	
Total shipments	7,700.00	8,100.00	8,800.00	9,200.00	9,499.90	8,825.00	8,291.70	7,864.60	8,005.20	7,585.80	
With Masked Models											
Revenues	786.20	875.20	1,008.78	1,216.17	1,333.90	2,163.21	1,984.33	2,261.31	1,190.10	1,184.49	
Sales	1,974	2,115	2,269	2,495	2,616	3,913	3,415	3,818	2,152	2,177	
Share to total revenues	0.25	0.29	0.31	0.29	0.31	0.49	0.50	0.60	0.28	0.33	0.36
Share to total sales	0.28	0.32	0.32	0.29	0.33	0.49	0.46	0.54	0.27	0.31	0.36
Share to total shipments	0.26	0.26	0.26	0.27	0.28	0.44	0.41	0.49	0.27	0.29	0.32
No Masked Models											
Revenues	595.19	681.32	671.22	803.63	906.61	1,620.89	1,577.39	2,010.16	1,188.27	1,183.43	
Sales	1,461.43	1,612.01	1,346.36	1,430.73	1,602.59	2,551.27	2,396.38	3,238.42	2,149.07	2,175.01	
Share to total revenues	0.19	0.22	0.21	0.19	0.21	0.37	0.40	0.53	0.28	0.33	0.29
Share to total sales	0.21	0.25	0.19	0.17	0.20	0.32	0.32	0.46	0.27	0.31	0.27
Share to total shipments	0.19	0.20	0.15	0.16	0.17	0.29	0.29	0.41	0.27	0.29	0.24

Revenues are in million US$ while sales and shipments are in thousand. Share to total shipments refers to sales/total shipments. Data Sources: Total revenue and total units sold in the US Market (NPD Group); total shipment (Association of Home Appliance Manufacturers).

Table 9: Market Share of Sampled Clothes Dryers, 2002-2010.

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	Ave.
US Market											
Total revenues	2,202.36	2,188.03	2,479.57	3,046.35	3,049.58	3,305.53	2,950.70	2,851.88	3,008.44	2,762.69	
Total sales	6,011.97	5,701.15	6,570.88	7,516.35	6,895.39	6,638.78	6,088.85	5,573.73	6,084.09	5,576.13	
Total shipments	6,892.00	7,334.00	7,922.00	8,158.00	7,974.00	7,554.00	6,973.00	6,484.00	6,551.00	6,147.00	
With Masked Models											
Revenues	560.78	641.67	683.68	850.79	936.00	1,046.53	1,327.34	1,408.86	1,524.81	1,458.90	
Sales	1,741.91	1,917.58	1,884.36	2,155.43	2,227.32	2,264.83	2,467.81	2,452.42	2,812.59	2,700.24	
Share to total revenues	0.25	0.29	0.28	0.28	0.31	0.32	0.45	0.49	0.51	0.53	0.37
Share to total sales	0.29	0.34	0.29	0.29	0.32	0.37	0.44	0.40	0.50	0.48	0.37
Share to total shipments	0.25	0.26	0.24	0.26	0.28	0.30	0.35	0.38	0.43	0.44	0.32
No Masked Models											
Revenues	411.81	463.20	435.54	573.55	632.66	771.10	1,058.08	1,254.47	1,388.90	1,337.26	
Sales	1,214.94	1,328.87	1,073.31	1,287.29	1,371.76	1,507.53	1,768.35	2,089.58	2,461.47	2,436.86	
Share to total revenues	0.19	0.21	0.18	0.19	0.21	0.23	0.36	0.44	0.46	0.48	0.29
Share to total sales	0.20	0.23	0.16	0.17	0.20	0.25	0.32	0.34	0.44	0.44	0.28
Share to total shipments	0.18	0.18	0.14	0.16	0.17	0.20	0.25	0.32	0.38	0.40	0.24

Revenues are in million US$ while sales and shipments are in thousand. Share to total shipments refers to sales/total shipments. Data Sources: Total revenue and total units sold in the US Market (NPD Group); total shipment (Association of Home Appliance Manufacturers).

Table 10: Market Share of Sampled Refrigerators, 2002-2010.

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	Ave.
US Market											
Total revenue	6,264.78	6,451.32	7,066.55	8,458.54	6,861.38	7,125.29	6,371.34	5,757.18	7,061.46	6,732.37	
Total sales	9,441.82	9,538.61	10,845.29	13,653.76	10,307.90	9,998.98	9,211.50	8,256.87	9,569.39	9,257.02	
Total shipments	9,744.00	10,021.00	10,913.00	11,135.00	11,077.00	10,399.00	9,328.00	8,397.00	9,369.00	8,981.00	
With Masked Models											
Revenues	1,468.05	1,605.75	1,775.48	2,126.66	2,236.09	3,464.53	2,722.82	2,823.89	3,339.54	2,983.74	
Sales	2,501	2,787	3,121	3,413	3,333	4,453	3,433	3,498	4,075	3,569	
Share to total revenues	0.23	0.25	0.25	0.25	0.33	0.49	0.43	0.49	0.47	0.44	0.36
Share to total sales	0.26	0.29	0.29	0.25	0.32	0.45	0.37	0.42	0.43	0.39	0.35
Share to total shipments	0.26	0.28	0.29	0.31	0.30	0.43	0.37	0.42	0.43	0.40	0.35
No Masked Models											
Revenues	1,169.32	1,185.19	1,045.06	1,157.34	1,273.75	2,097.53	1,762.98	1,917.41	2,258.95	1,996.81	
Sales	1,732.02	1,830.93	1,617.43	1,588.95	1,678.89	2,241.76	1,854.52	2,086.32	2,369.66	2,031.72	
Share to total revenues	0.19	0.18	0.15	0.14	0.19	0.29	0.28	0.33	0.32	0.30	0.24
Share to total sales	0.18	0.19	0.15	0.12	0.16	0.22	0.20	0.25	0.25	0.22	0.19
Share to total shipments	0.18	0.18	0.15	0.14	0.15	0.22	0.20	0.25	0.25	0.23	0.19

Revenues are in million US$ while sales and shipments are in thousand. Share to total shipments refers to sales/total shipments. Data Sources: Total revenue and total units sold in the US Market (NPD Group); total shipment (Association of Home Appliance Manufacturers).

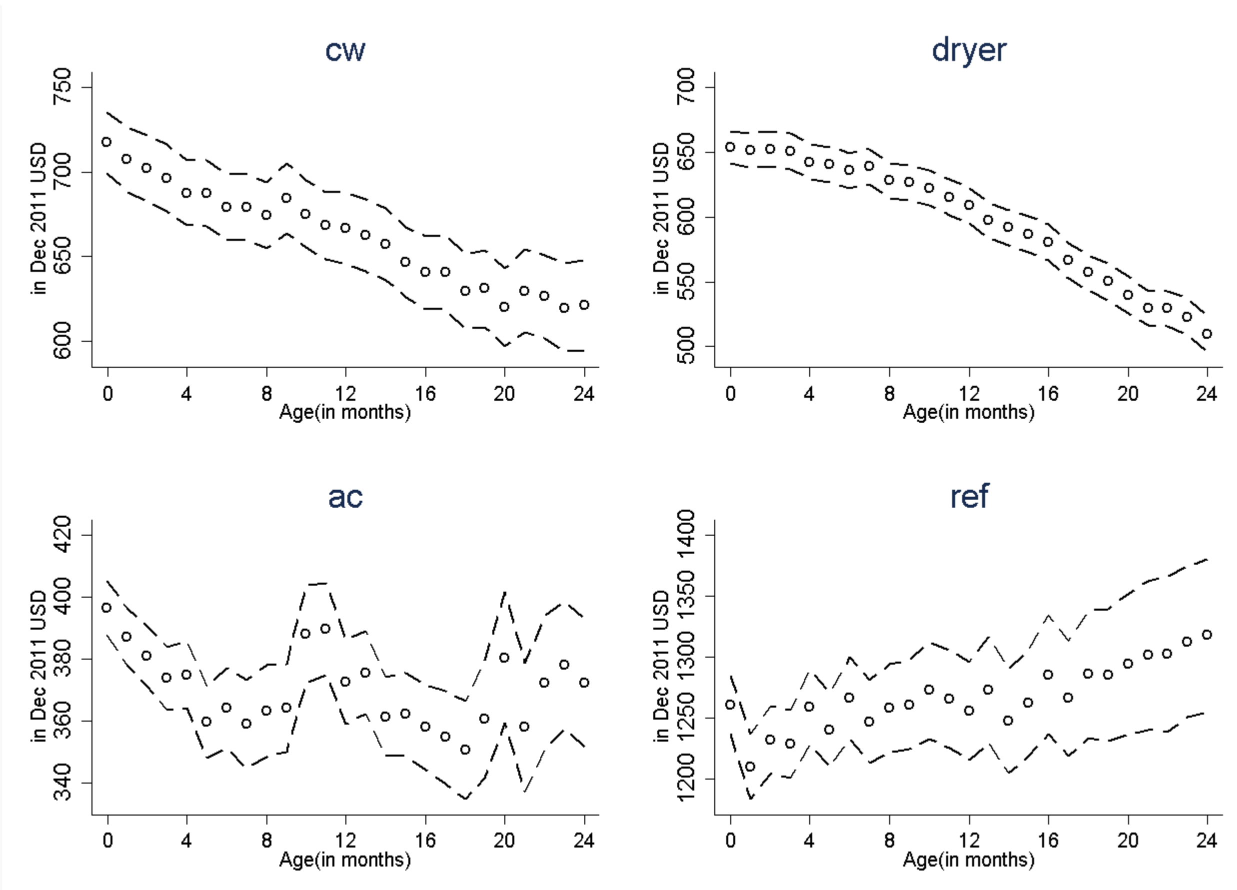
Table 11: Market Share of Sampled Room Airconditioners, 2002-2010.

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	Ave
US Market											
Total revenue	6,264.78	6,451.32	7,066.55	8,458.54	6,861.38	7,125.29	6,371.34	5,757.18	7,061.46	6,732.37	
Total sales	9,441.82	9,538.61	10,845.29	13,653.76	10,307.90	9,998.98	9,211.50	8,256.87	9,569.39	9,257.02	
Total shipments	9,744.00	10,021.00	10,913.00	11,135.00	11,077.00	10,399.00	9,328.00	8,397.00	9,369.00	8,981.00	
With Masked Models											
Revenues	1,468.05	1,605.75	1,775.48	2,126.66	2,236.09	3,464.53	2,722.82	2,823.89	3,339.54	2,983.74	
Sales	2,501	2,787	3,121	3,413	3,333	4,453	3,433	3,498	4,075	3,569	
Share to total revenues	0.23	0.25	0.25	0.25	0.33	0.49	0.43	0.49	0.47	0.44	0.36
Share to total sales	0.26	0.29	0.29	0.25	0.32	0.45	0.37	0.42	0.43	0.39	0.35
Share to total shipments	0.26	0.28	0.29	0.31	0.30	0.43	0.37	0.42	0.43	0.40	0.35
No Masked Models											
Revenues	1,169.32	1,185.19	1,045.06	1,157.34	1,273.75	2,097.53	1,762.98	1,917.41	2,258.95	1,996.81	
Sales	1,732.02	1,830.93	1,617.43	1,588.95	1,678.89	2,241.76	1,854.52	2,086.32	2,369.66	2,031.72	
Share to total revenues	0.19	0.18	0.15	0.14	0.19	0.29	0.28	0.33	0.32	0.30	0.24
Share to total sales	0.18	0.19	0.15	0.12	0.16	0.22	0.20	0.25	0.25	0.22	0.19
Share to total shipments	0.18	0.18	0.15	0.14	0.15	0.22	0.20	0.25	0.25	0.23	0.19

Revenues are in million US$ while sales and shipments are in thousand. Share to total shipments refers to sales/total shipments. Data Sources: Total revenue and total units sold in the US Market (NPD Group); total shipment (Association of Home Appliance Manufacturers).

Appendix B Market Average Price Trend Across Vintages

Figure 7: Market Average Price Trend Across Vintages, Select Appliances, Jan. 2002- Dec. 2011.



Note: cw= Clothes Washers; dryer = Clothes Dryers; ac = Room Airconditioners; ref = Refrigerators. All prices are in Dec. 2011 US$.
Source: The NPD Group.

Appendix C Validation of Price-Based Estimates of Overall Quality

To validate price-based estimates of overall quality, it helps to identify whether particular attributes, like energy efficiency, are associated with it. For clothes washers, two observable characteristics directly contribute to measures energy efficiency metrics: 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 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, with considerable uptakes around the imposition of more stringent ME and ES standards(Figure 8). For example, the shares of clothes washers that have spin speed of 649 rpms and lower fell around January 2004 and 2007, while 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.

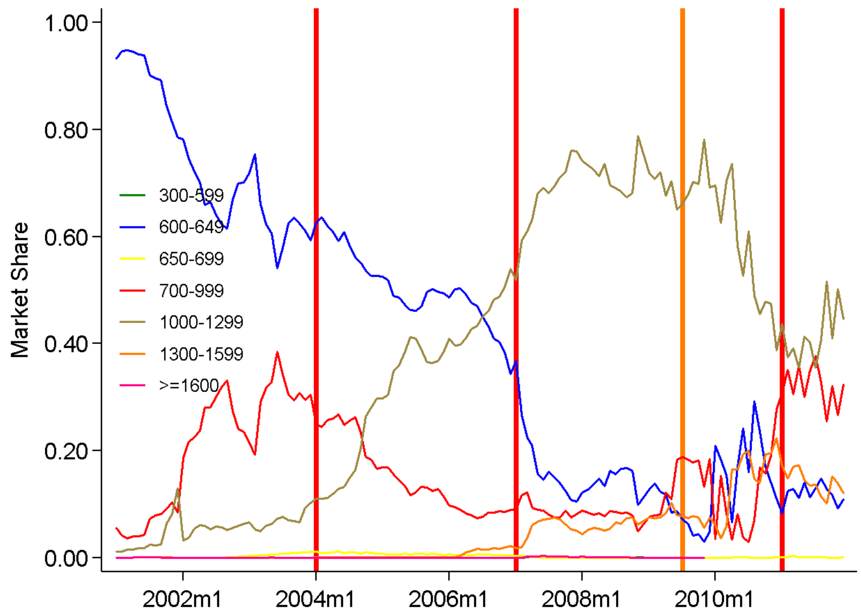
While energy efficiency improves over time, we also observe improvements in the quality of each model that do not necessarily contribute to the energy efficiency metric for clothes washers. Figures 9 to 10 illustrate the trend of market share of characteristics that affect the cleanliness of clothes (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 9 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 10). Particularly around 2004, washers that have 11-15 wash cycle options increased significantly, taking more than 20 percent 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.

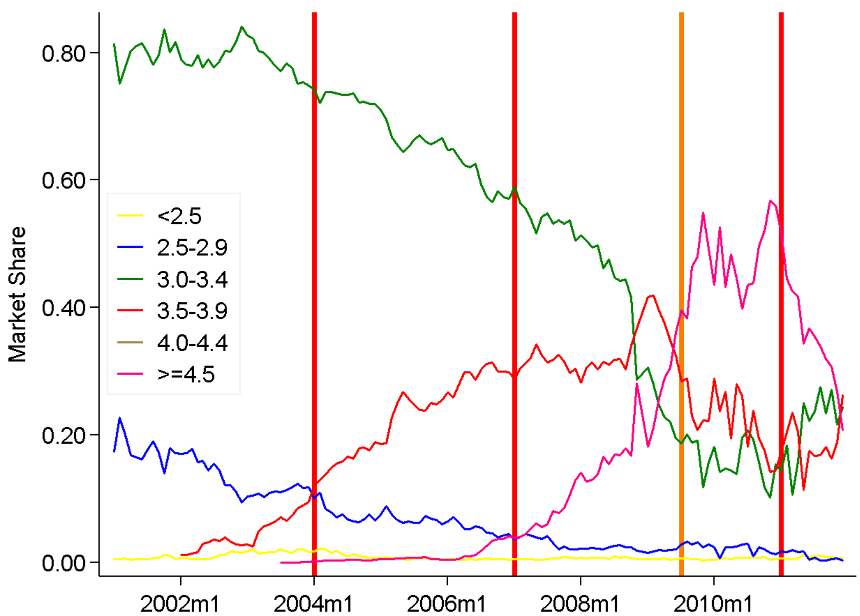
The 2011 policy change had minimal or counter-intuitive effect on most characteristics for which we have information on. Newer features appeared during this period about which are not observed in our data. These include steam wash technology and direct drive technology that is reportedly quieter than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

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

(a) Revolutions per minute



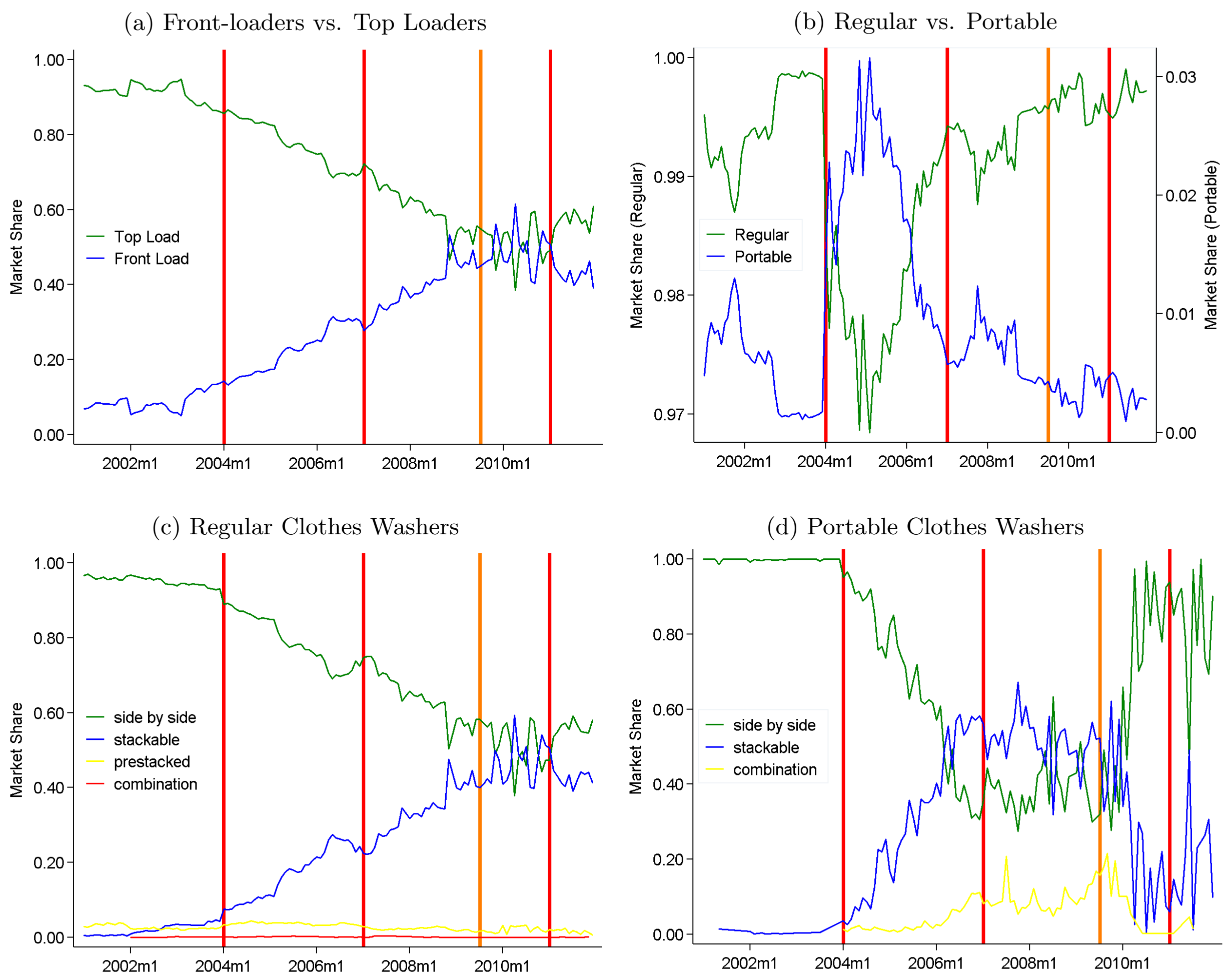
(b) Volume/Capacity



Capacity/volume is 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.

Figure 9: Market share by product category, space-saving characteristics, Jan. 2001-Dec. 2011

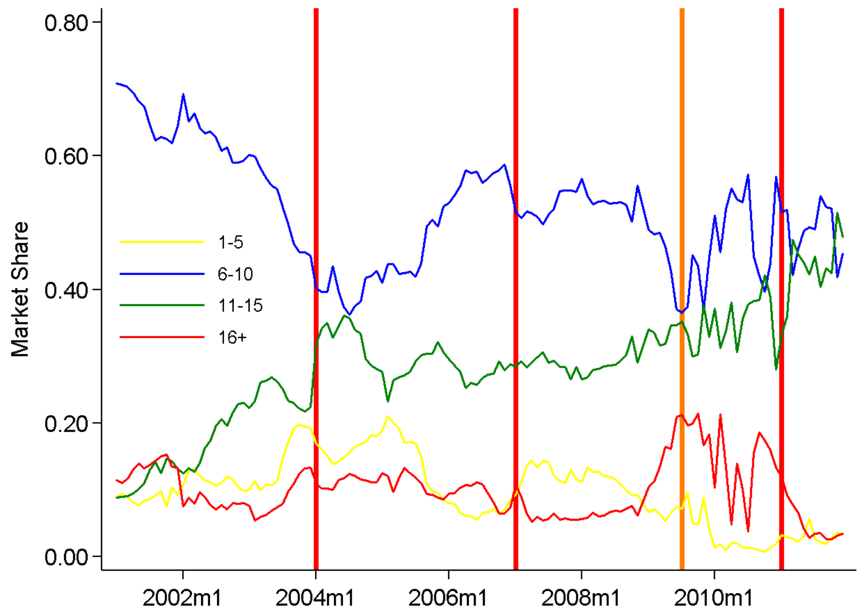


The red vertical solid lines pertain to the simultaneous ME and ES policy changes in January of 2004, 2007 and 2011; while the orange vertical solid line pertains to the ES policy change in July 2009.

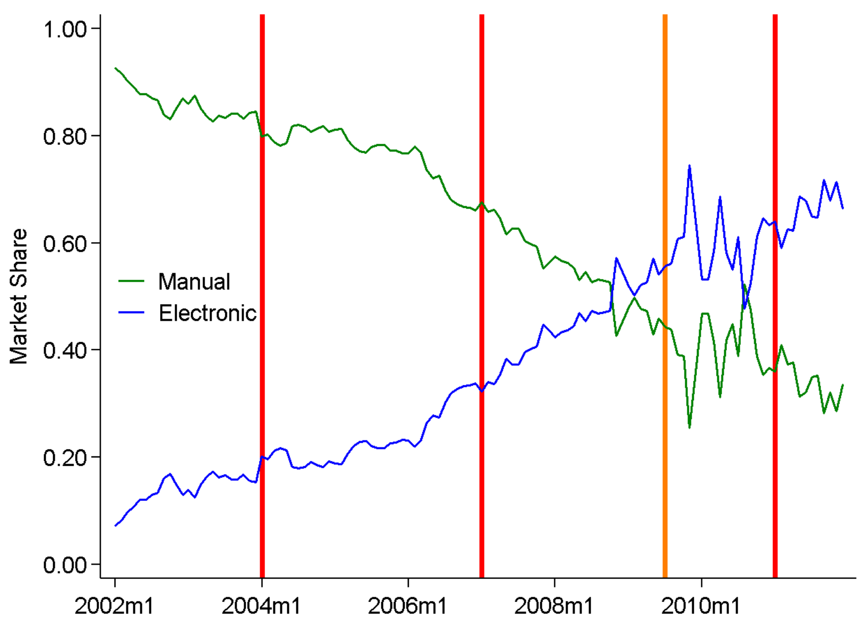
Source: The NPD Group.

Figure 10: 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



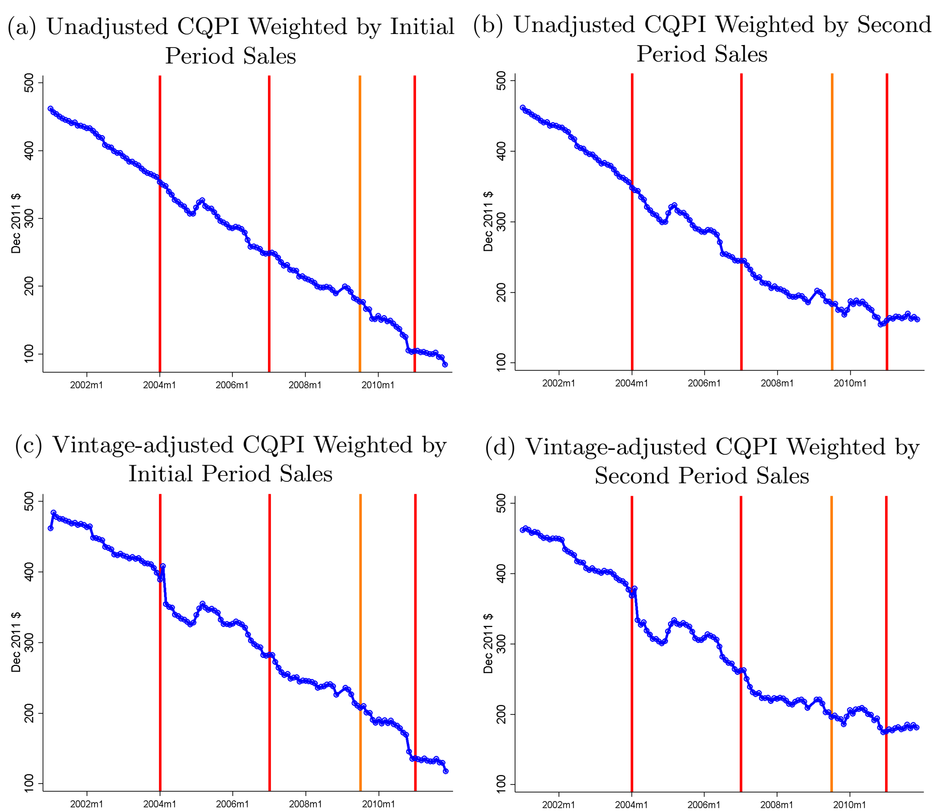
The red vertical solid lines pertain to the simultaneous ME and ES policy changes in January of 2004, 2007 and 2011; while the orange vertical solid line pertain to the ES policy change in July 2009.

Source: The NPD Group.

Appendix D The CQPI With Different 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 (see Figure 11).

Figure 11: CQPI Trends Under Different Weights



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.

*Source:*Authors' calculation.

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

To check the robustness of the estimated average effect of a policy change, 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 12 summarizes the results of the regression for the percentage change in the CQPI, quality index and level change in estimated welfare. Columns labeled (1)-(2) include clothes washers and refrigerators, and (3) adds room ACs in the sample. Month x Ref and Month x AC are intersections of month and appliance dummies for refrigerators and room ACs, respectively, to control for the fairly robust seasonality that we observed for the appliances in each of the key variable. Results are qualitatively similar with what we find using the 6-month pre- and post-implementation period.

Table 12: RESULTS FROM ESTIMATING THE AVERAGE EFFECT OF THE POLICY CHANGE

Variables	Dependent Variable								
	Δ CQPI			**Δ Quality**			**Δ Welfare**		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
ME and ES	**-1.057**	**-0.791**	**-1.314**	**0.905**	**0.835**	**0.803**	**-0.926**	**-3.023**	**2.751**
	(1.026)	**(0.939)**	**(0.979)**	**(1.136)**	**(1.252)**	**(1.237)**	**(4.811)**	**(4.176)**	**(3.496)**
ES Only	**-0.395**	**-0.347**	**-0.637**	**0.115**	**0.221**	**0.343**	**2.074**	**1.585**	**3.990***
	(0.503)	**(0.486)**	**(0.634)**	**(0.639)**	**(0.598)**	**(0.766)**	**(2.332)**	**(2.220)**	**(2.152)**
Constant	-5.608***	0.152	1.632*	4.876	0.348	-3.187*	14.561***	6.481*	1.887
	(0.114)	(0.441)	(0.907)	(0.177)	(0.703)	(1.666)	(0.621)	(3.519)	(5.118)
Appliance FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month x Ref	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Month x AC	No	No	Yes	No	No	Yes	No	No	Yes
R-squared	0.670	0.747	0.675	0.533	0.591	0.594	0.687	0.758	0.643
Adj. R-squared	0.316	0.414	0.447	0.031	0.052	0.309	0.350	0.441	0.392
Observations	221	221	333	221	221	333	221	221	333

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, assuming the effect of policy change 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)-(2) include clothes washers and refrigerators, and (3) adds room ACs in the sample. Month x Ref and Month x AC are intersections of month and appliance dummies for refrigerators and room ACs, respectively. Robust standard errors are in parentheses. ***, **, * represent statistical significance at 1, 5, and 10 percent level, respectively.

Appendix F List of Manufacturers and Brands in the NPD Data

Table 13: List of Manufacturers and their Respective Brand

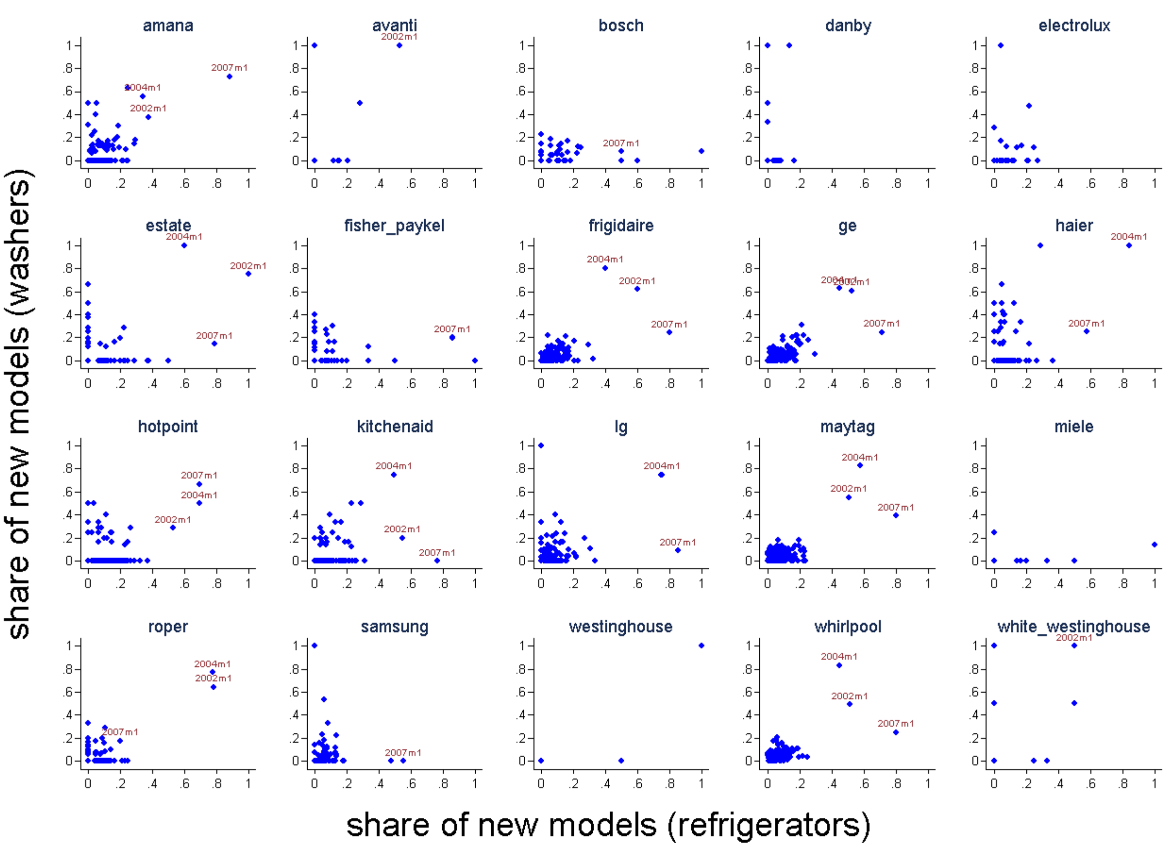
Manufacturer	Brands	
Whirlpool	Amana	Magic Chef
	Estate	Maytag
	Inglis	Roper
	KitchenAid	Whirlpool
General Electric	Ariston	
	GE	
	GE Profile	
	Hotpoint	
Electrolux	Electrolux	
	Frigidaire	
	Westinghouse	
	White Westinghouse	
LG	LG	
Others	Asko	Fagor
	Avanti Pro	Fisher & Paykel
	Bosch	Haier
	Danby	Miele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

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.
Source: Spurlock (2013).

Appendix G 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 2007 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 brand level. We find the same significant correlation particularly for major brands of washers and refrigerators like GE, LG, Maytag, and Whirlpool (Figure 12).

Figure 12: Correlation in the share of new models to total stock units between washers and refrigerators, brand level, monthly, 2001-2011



Source: The NPD Group

Appendix H Results from Including Masked Models in the Sample

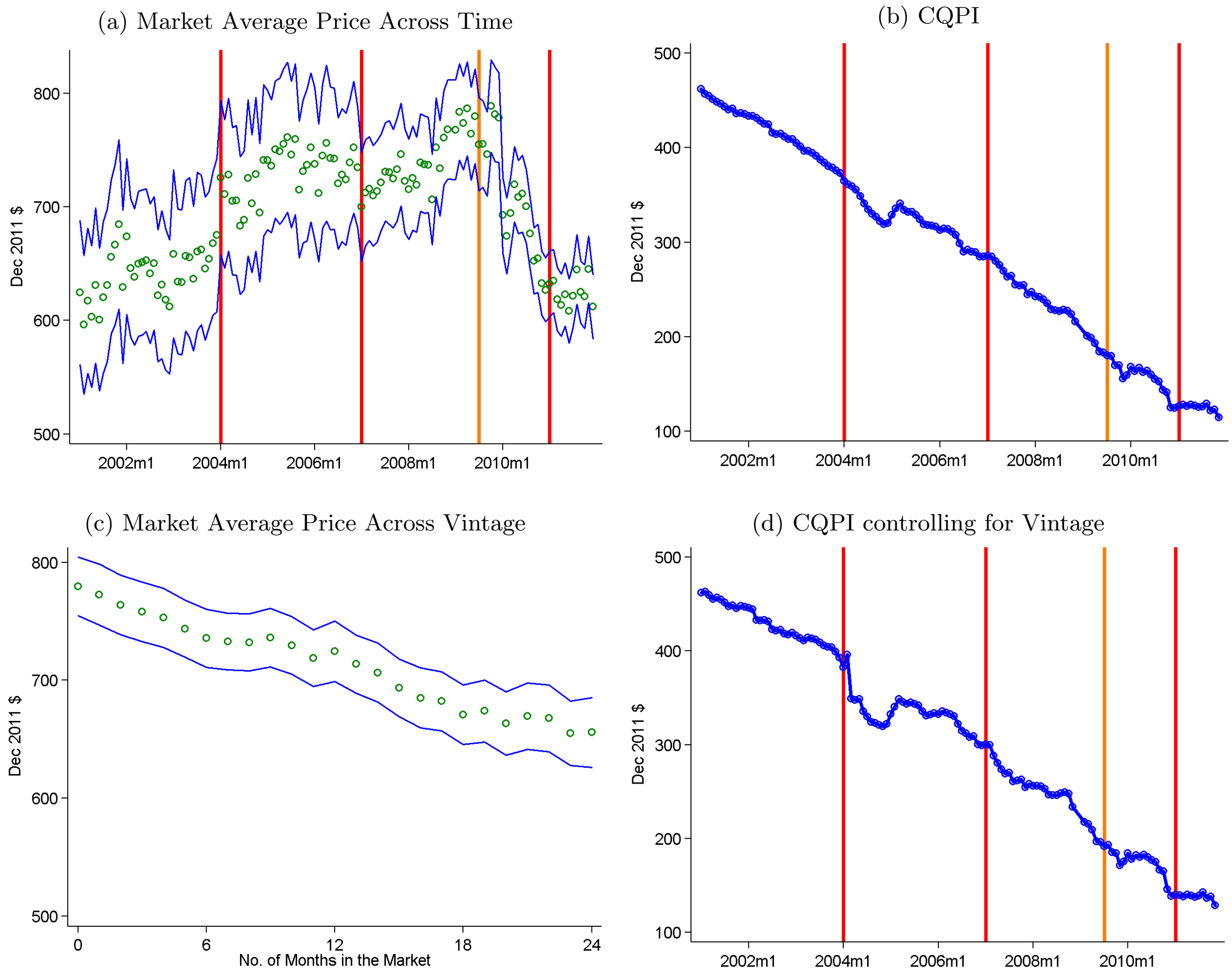
To address the potential bias introduced by including the 35 percent masked models in the data, we conduct a series of robustness checks. This include repeating all the important figures in the analysis and the regressions of price against the average vintage within and between firms, both at the brand and manufacturer levels (equation 8). The results from estimating equation 8 without masked models are presented in Table 14. 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 14: Regression Results: Dependent Variable – Unit Price, Clothes Washers (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^2 (within group)	0.373	0.372
Observations	22,445	22,755

The table reports the results from estimating equation 9 without the interaction effects *using unmasked models only.* Column (1) estimates the effects of within- and between-brands average vintage, and column (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.

Figure 13: Market Average Price and CQPI Trends, Clothes Washers (Unmasked Models Only)



The figure shows the average market price and CQPI trends *using unmasked models only.* Panel (a) shows sales-weighted average prices and 95 percent 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.

Source: Monthly sales and revenues of clothes washers sold in the US between 2001-2011 (The NPD Group); CQPI (Authors' calculation).

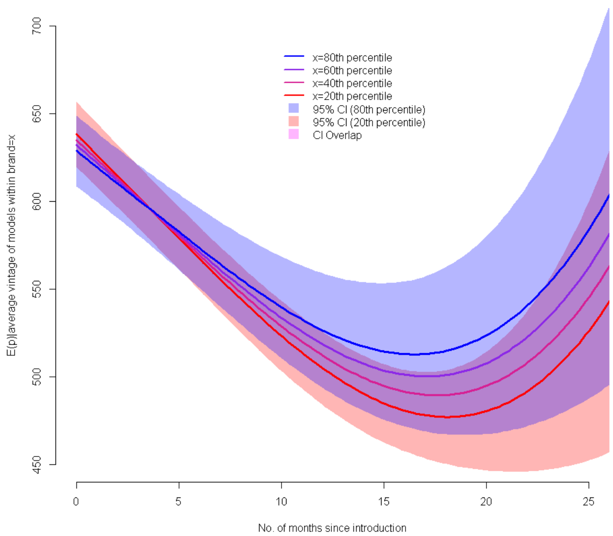
Appendix I Within and Between Brands Competition and Price Trends for Clothes Washers

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 14 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 15 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).

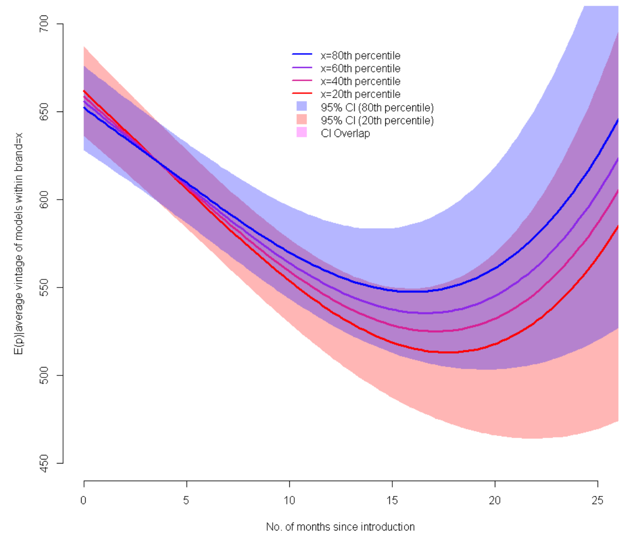
We also predict the price trend of a typical washer at different average vintage *within the same manufacturer* and *between manufacturers*. Figure 16 shows the predicted price of a typical clothes washer, holding average vintage of models *within the same manufacturer* constant at about 9 months (20th percentile), 11 months (40th percentile), 13 months (60th percentile) and 16 months (80 percentile). Figure 17 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 14: Life Cycle Pricing of Clothes Washers Under Different Within-Brand Average Vintage

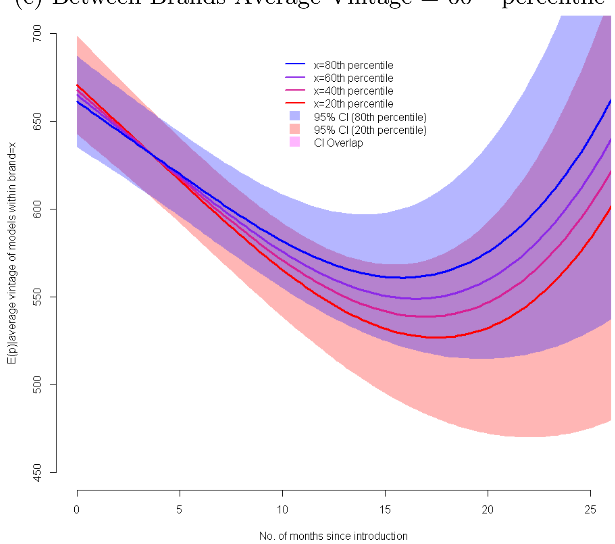
(a) Between Brands Average Vintage = 20^{th} percentile



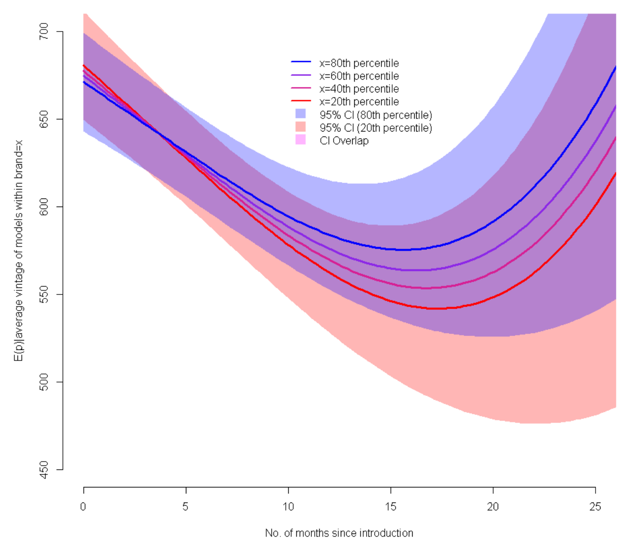
(b)Between Brands Average Vintage = 40^{th} percentile



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



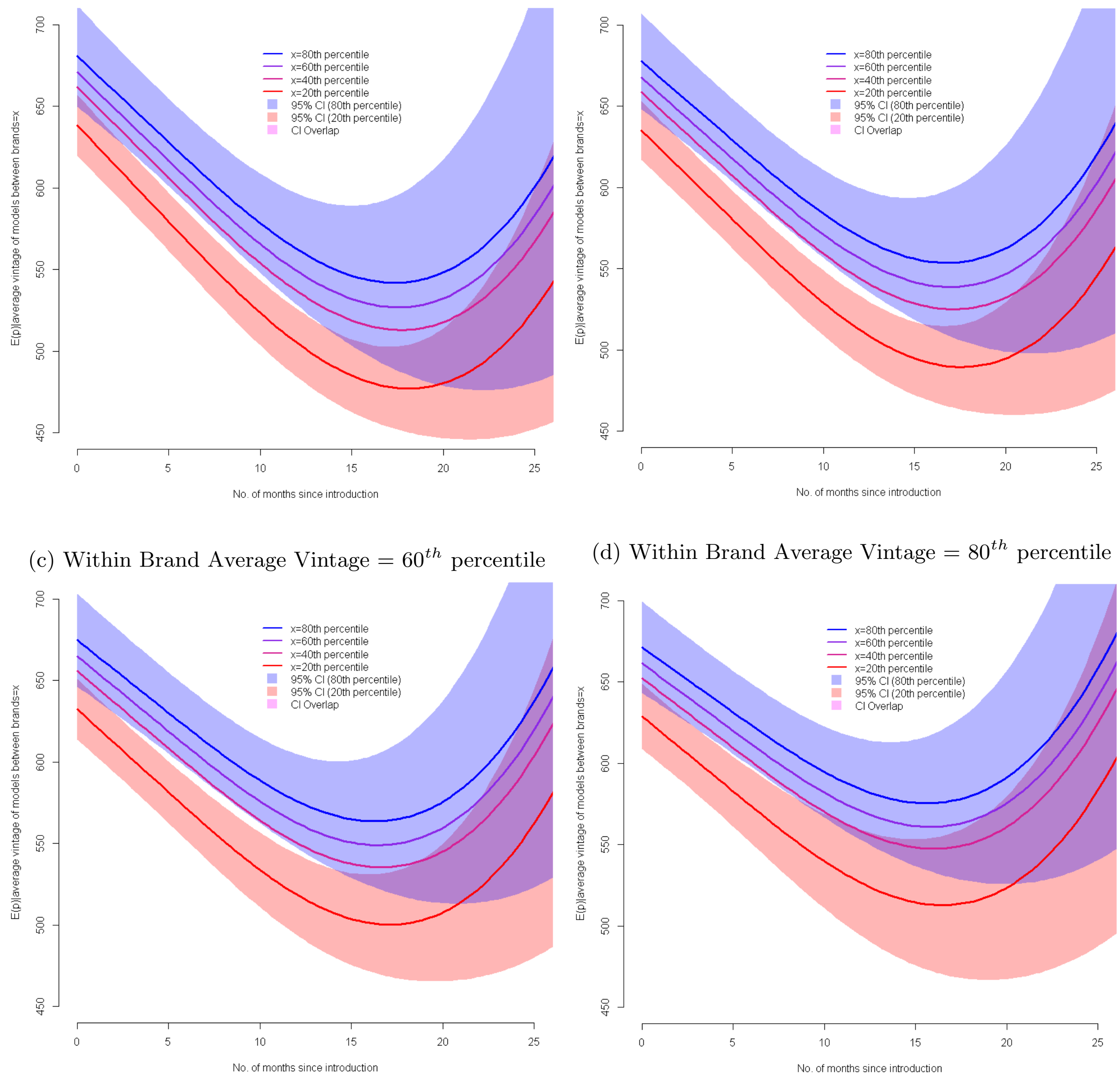
(d) Between Brands Average Vintage = 80^{th} percentile



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-brands average vintage, the 20th, 40th, 60th and 80th percentile correspond to 9.62, 12.54, 13.67, and 14.90, respectively.

Source: Authors' calculations.

Figure 15: 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

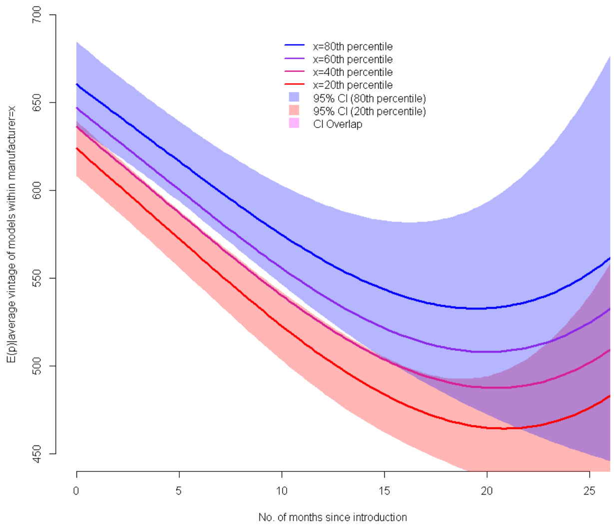
(d) Within Brand Average Vintage = 80^{th} percentile

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-brands 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-brands average vintage, the 20th, 40th, 60th and 80th percentile correspond to 7.71, 10.67. 13.32 and 16.58, respectively.

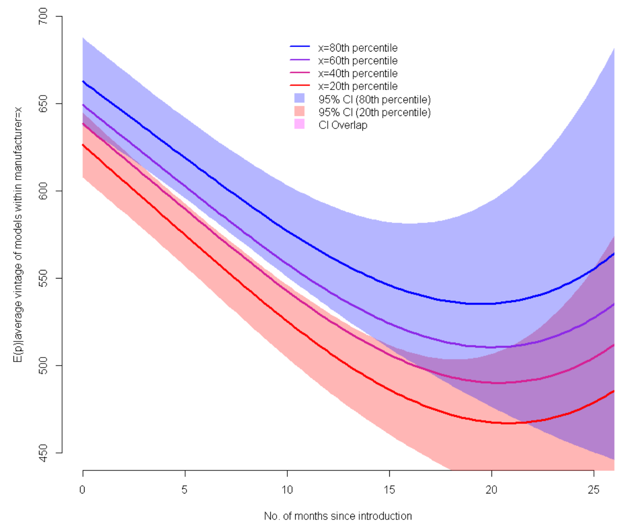
Source: Authors' calculations.

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

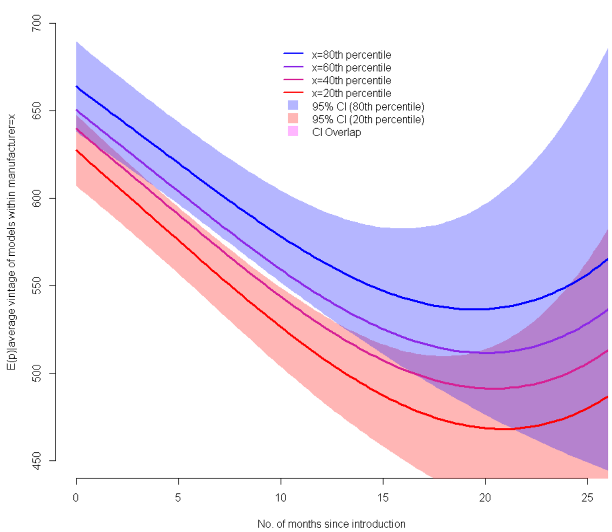
(a) Between Manufacturers Average Vintage = 20^{th} percentile



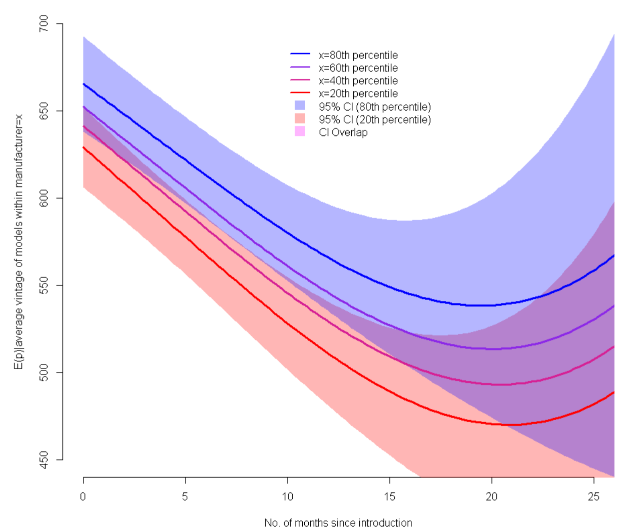
(b)Between Manufacturers Average Vintage = 40^{th} percentile



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



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

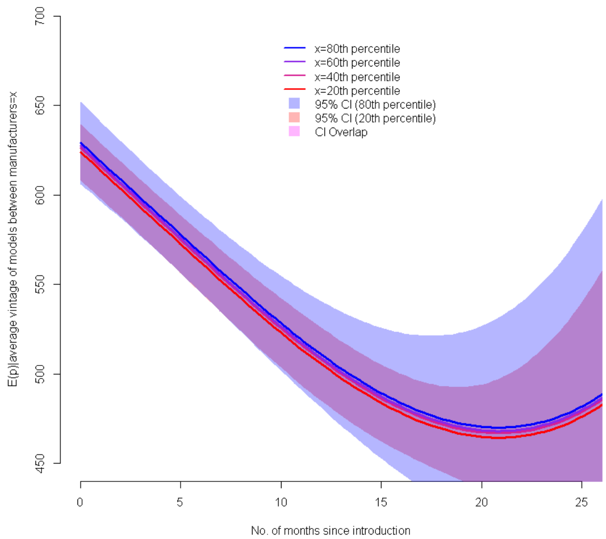


The figure shows that trend in the predicted price of a representative clothes washer using equation 9 during its first two years. We estimate equation 9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a within-manufacturer average vintage of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

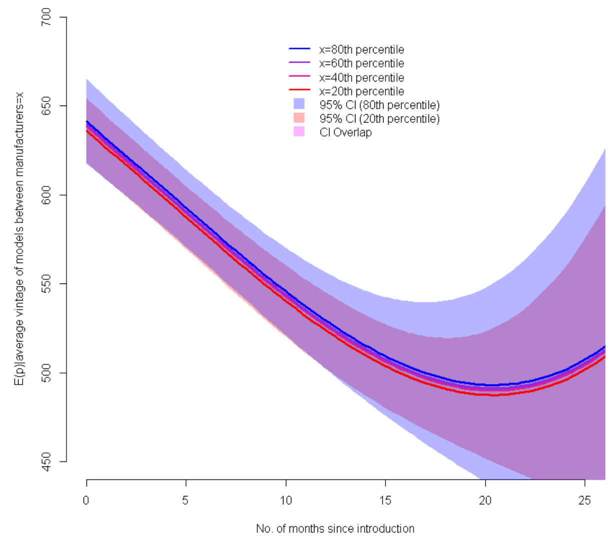
Source: Authors' calculations.

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

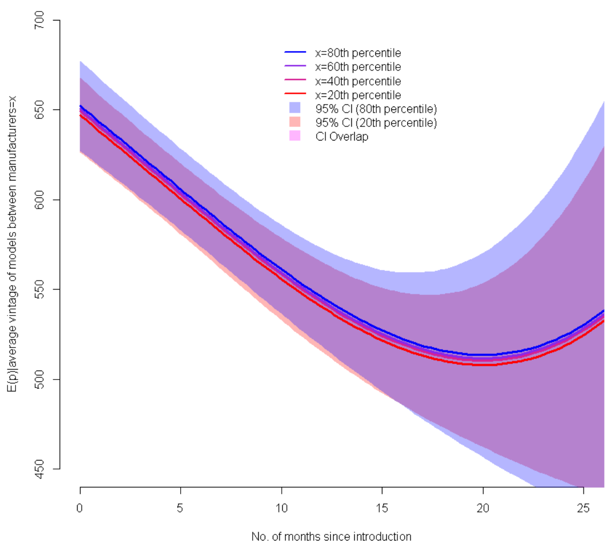
(a) Within Manufacturer Average Vintage = 20^{th} percentile



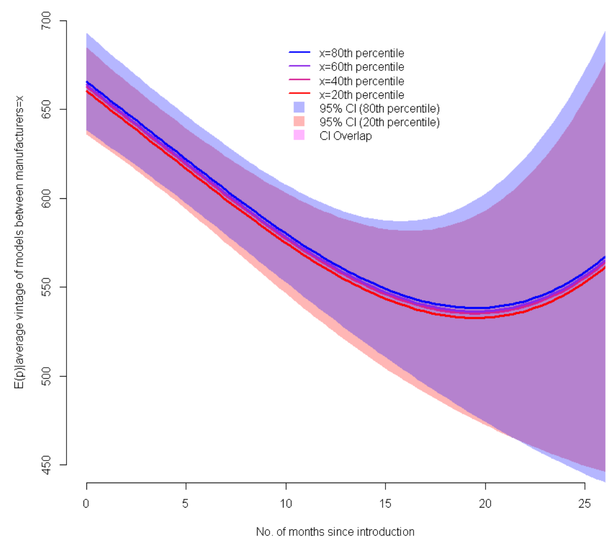
(b) Within Manufacturer Average Vintage = 40^{th} percentile



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



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



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: Authors' calculations.

Appendix J 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 ME and ES certification change during the study period, although refrigerators had 2004 and 2007 ES policy changes. This section plots predicted price using estimates from equation 9 for these appliances.

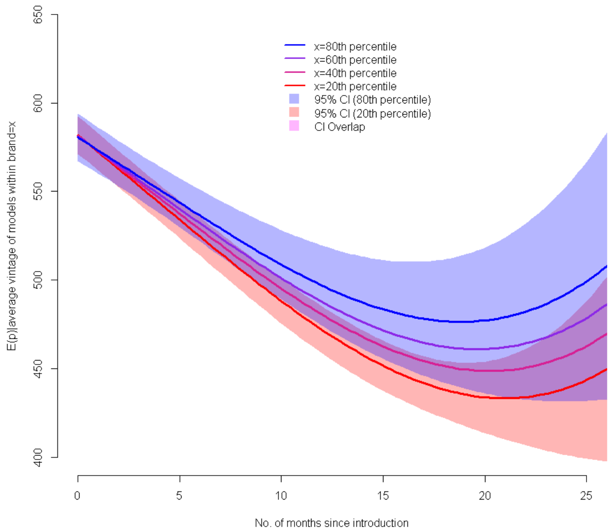
J.A Clothes Dryers

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 18 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 19 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).

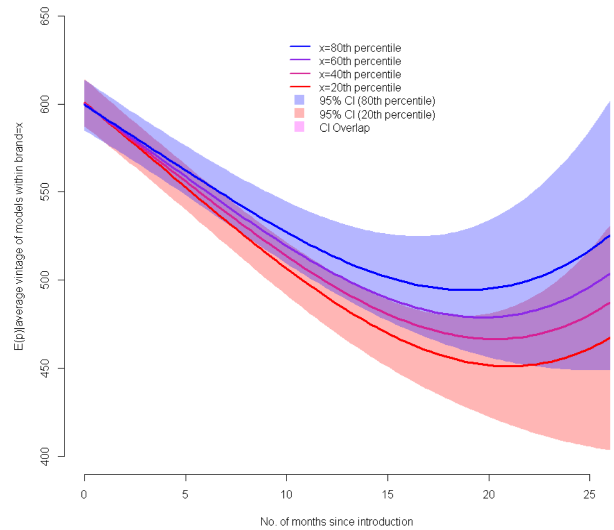
We also predict the price trend of a typical dryer at different average vintage within the same manufacturer and between manufacturers. Figure 20 shows the predicted price of a typical clothes dryer, holding average vintage of models within the same manufacturer constant at about 10 months (20th percentile), 13 months (40th percentile), 15 months (60th percentile) and 17 months (80 percentile). Figure 21 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 18: Life Cycle Pricing of Clothes Dryers Under Different Within-Brand Average Vintage

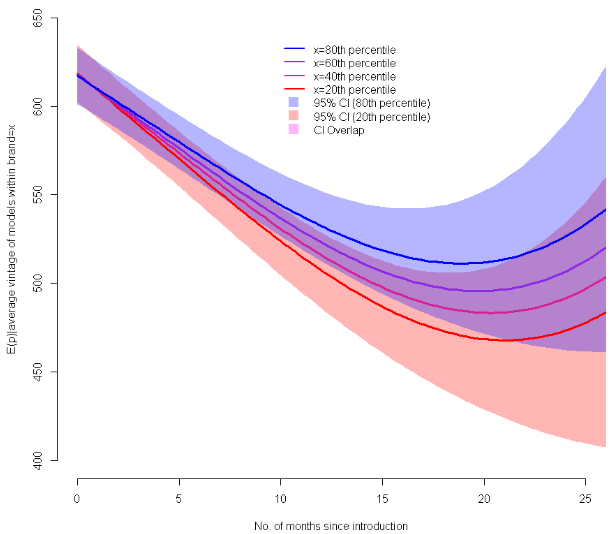
(a) Between Brands Average Vintage = 20^{th} percentile



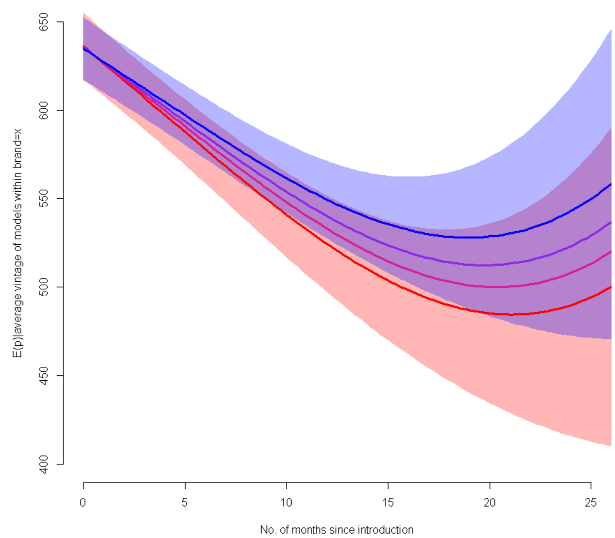
(b)Between Brands Average Vintage = 40^{th} percentile



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



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

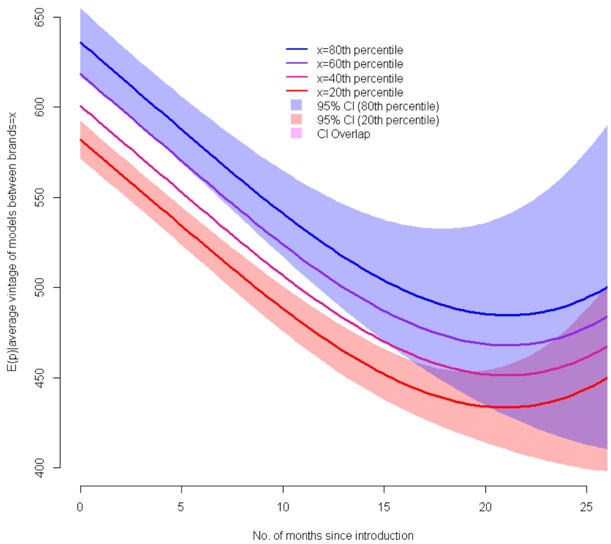


The figure shows the trend in the predicted price of a representative clothes dryer using equation 9 during its first two years. We estimate equation 9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a within-brand average vintage of clothes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

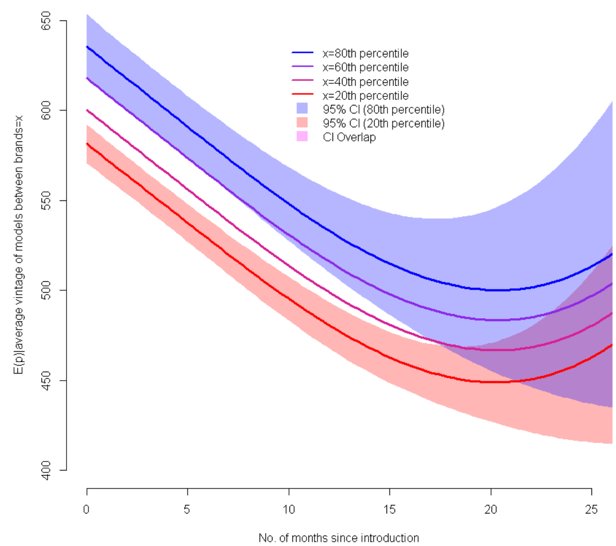
Source: Authors' calculations.

Figure 19: Life Cycle Pricing of Clothes Dryers Under Different Between-Brands Average Vintage

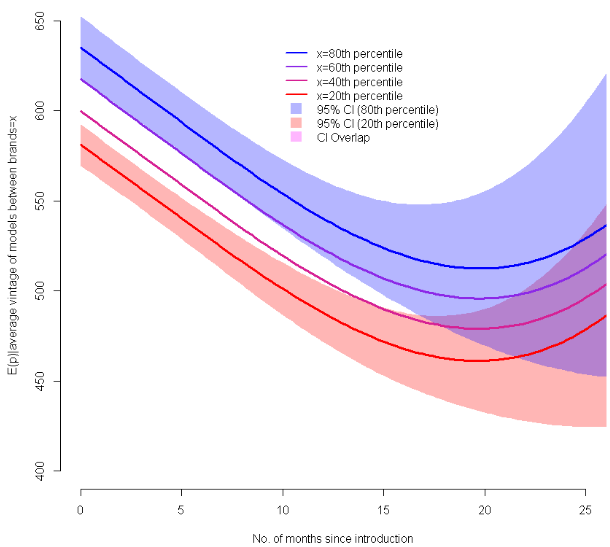
(a) Within Brand Average Vintage = 20^{th} percentile



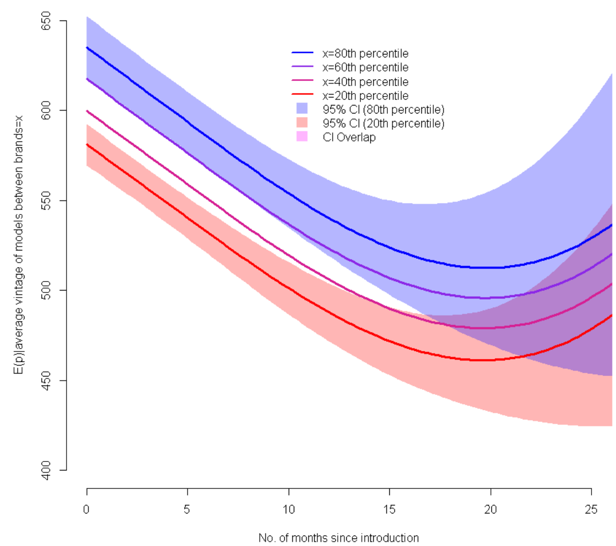
b)Within Brand Average Vintage = 40^{th} percentile



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



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

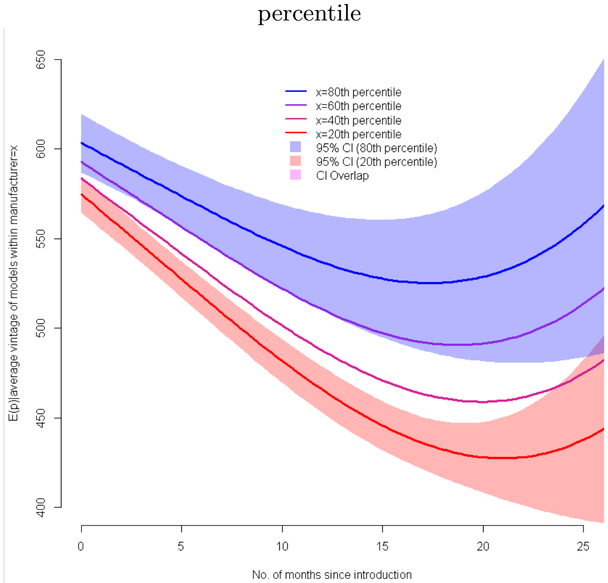


The figure shows the trend in the predicted price of a representative clothes dryer using equation 9 during its first two years. We estimate equation 9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a between-brands average vintage of clothes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

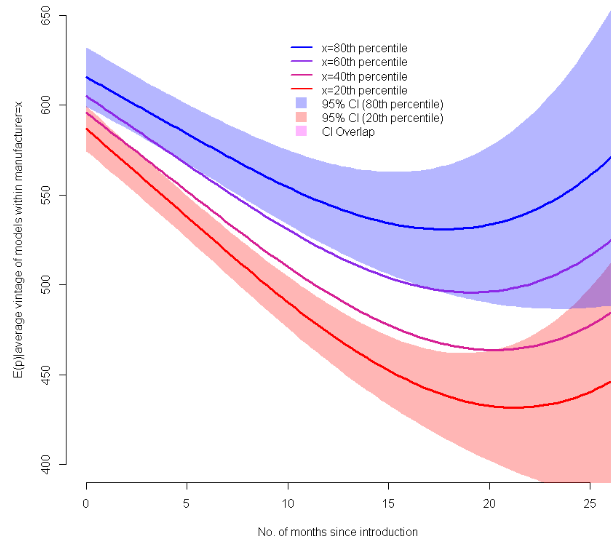
Source: Authors' calculations.

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

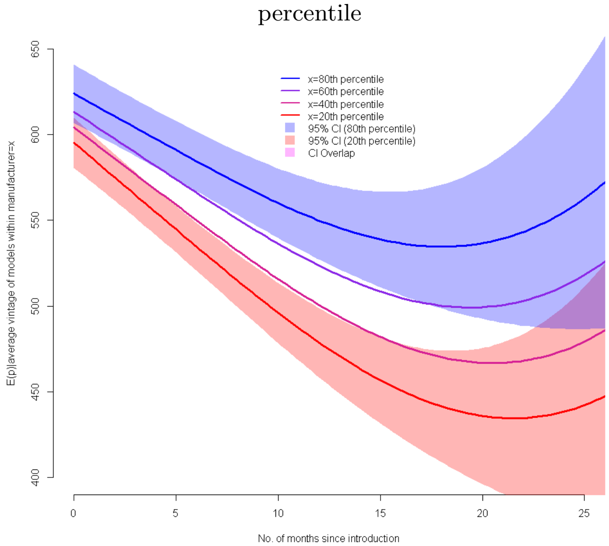
(a) Between Manufacturers Average Vintage = 20^{th} percentile



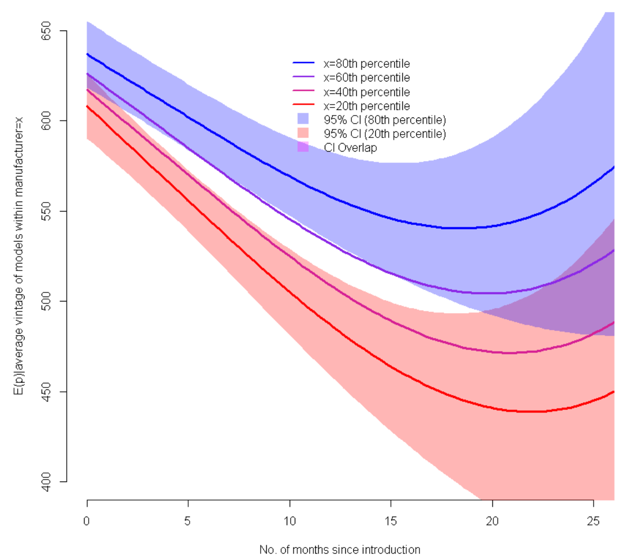
(b)Between Manufacturers Average Vintage = 40^{th} percentile



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



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

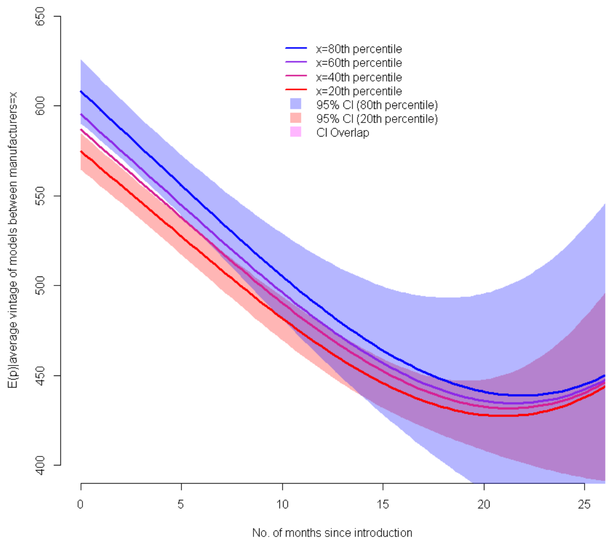


The figure shows the trend in the predicted price of a representative clothes dryer using equation 9 during its first two years. We estimate equation 9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a within-manufacturer average vintage of clothes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

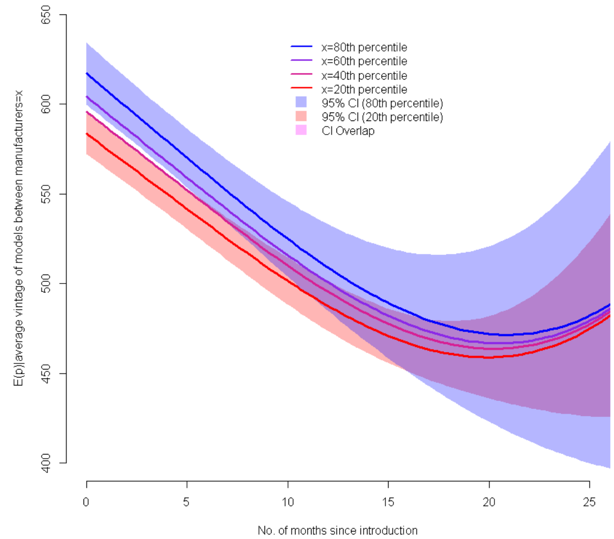
Source: Authors' calculations.

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

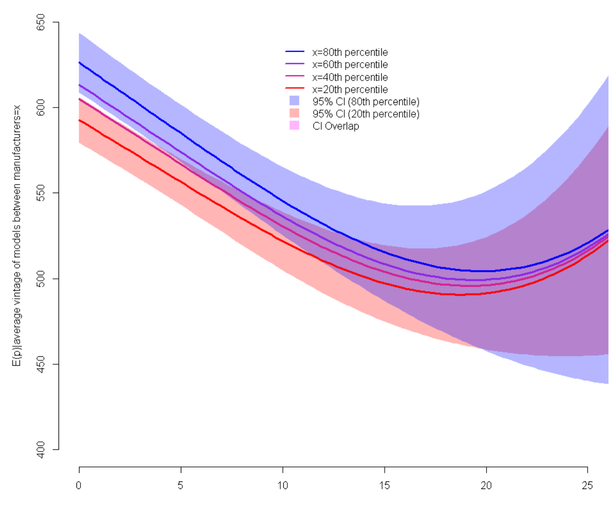
(a) Within Manufacturer Average Vintage = 20^{th} percentile



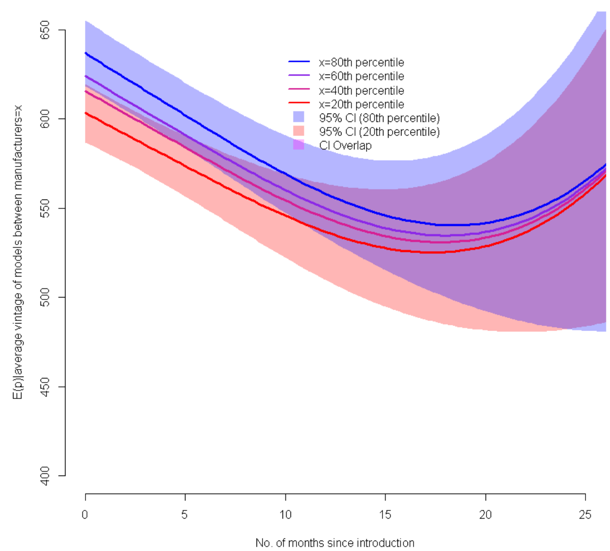
(b) Within Manufacturer Average Vintage = 40^{th} percentile



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



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



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-manufacturers average vintage of clothes dryer. The 20th, 40th, 60th and 80th percentile of between-manufacturers 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: Authors' calculations.

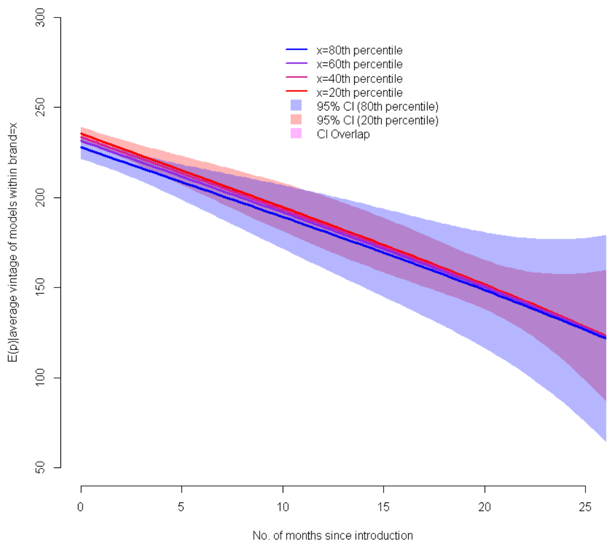
J.B Room Airconditioners

We use the estimates from equation 9 to predict the price trend of typical room AC holding average vintage of models within a brand constant. Figure 22 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 23 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).

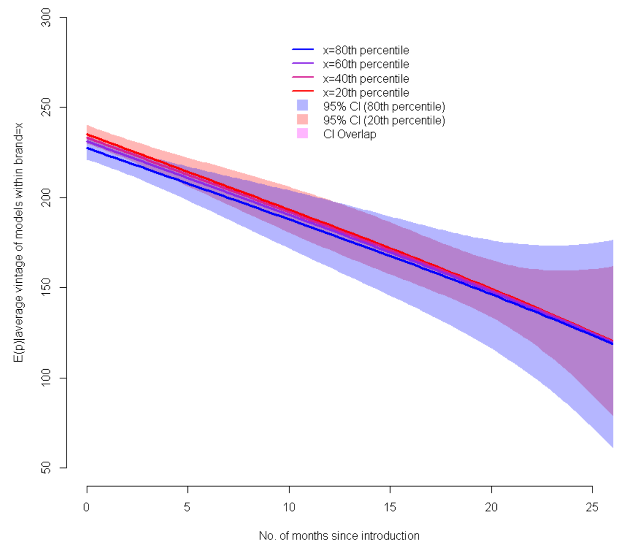
We also predict the price trend of a typical room AC at different average vintage within the same manufacturer and between manufacturers. Figure 24 shows the predicted price of a typical room AC, holding average vintage of models within the same manufacturer constant at about 5 months (20th percentile), 9 months (40th percentile), 13 months (60th percentile) and 19 months (80 percentile). Figure 25 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 22: Life Cycle Pricing of Room ACs Under Different Within-Brand Average Vintage

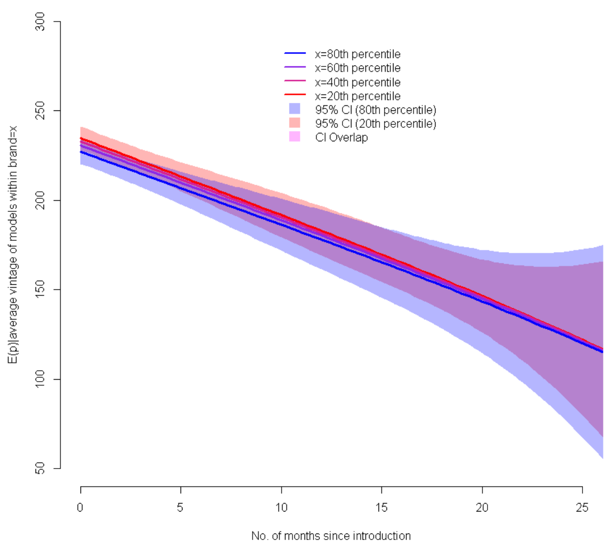
(a) Between Brands Average Vintage = 20^{th} percentile



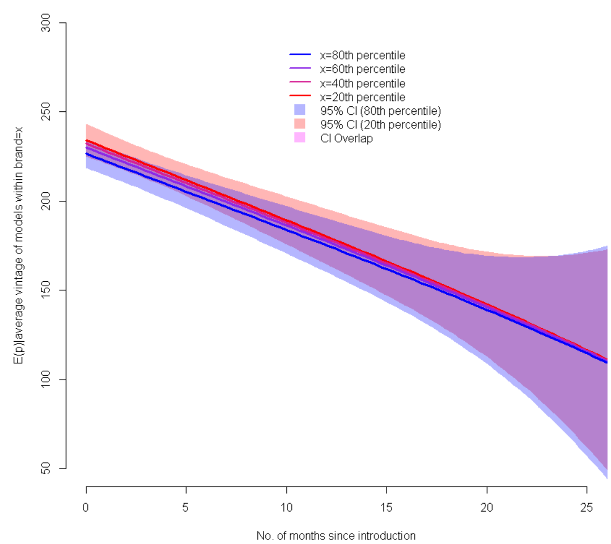
(b)Between Brands Average Vintage = 40^{th} percentile



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



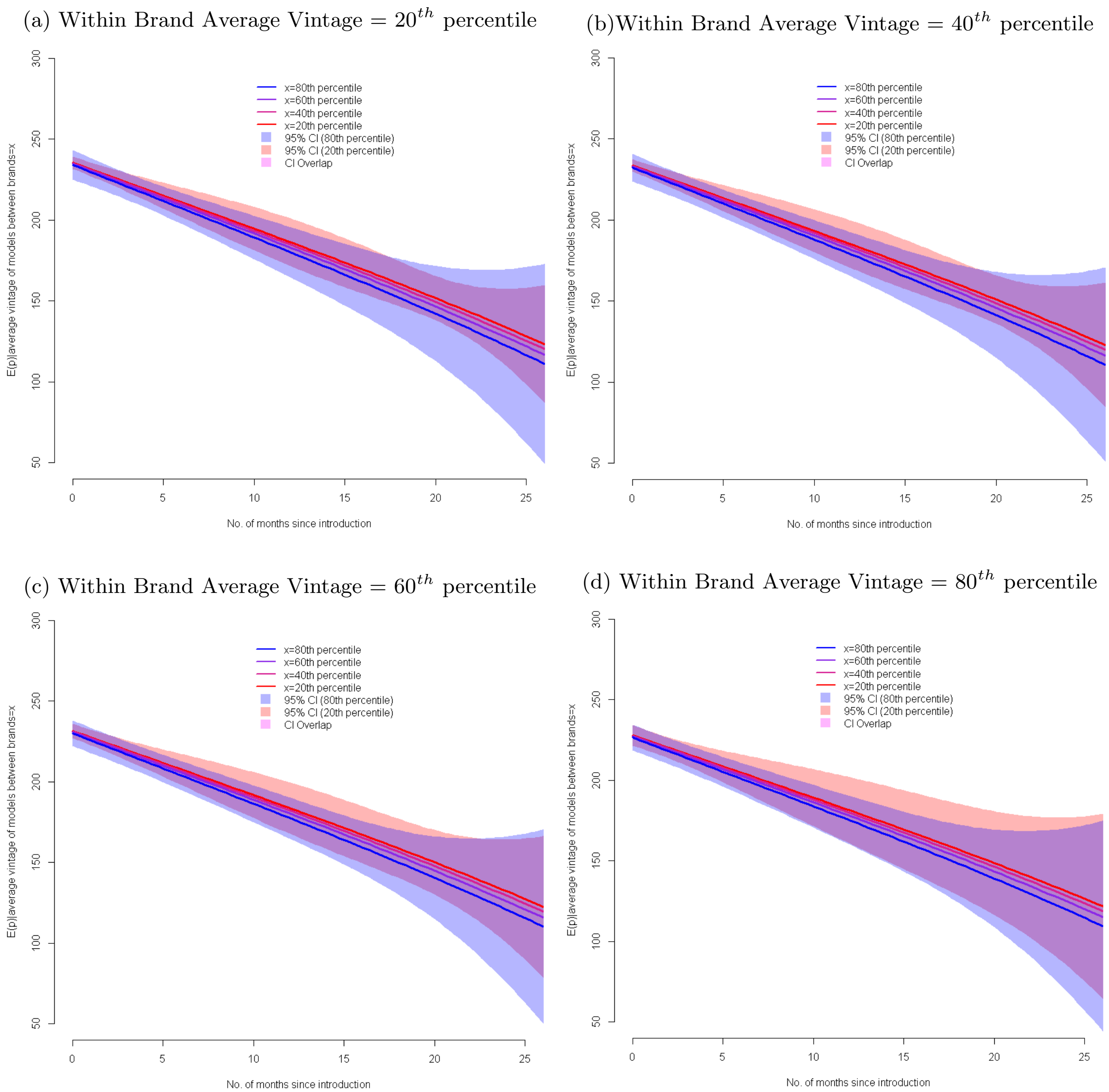
(d) Between Brands Average Vintage = 80^{th} percentile



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-brands average vintage, the 20th, 40th, 60th and 80th percentile correspond to 7.22, 9.08, 11.38, and 14.92 respectively.

Source: Authors' calculations.

Figure 23: Life Cycle Pricing of Room ACs Under Different Between-Brands Average Vintage

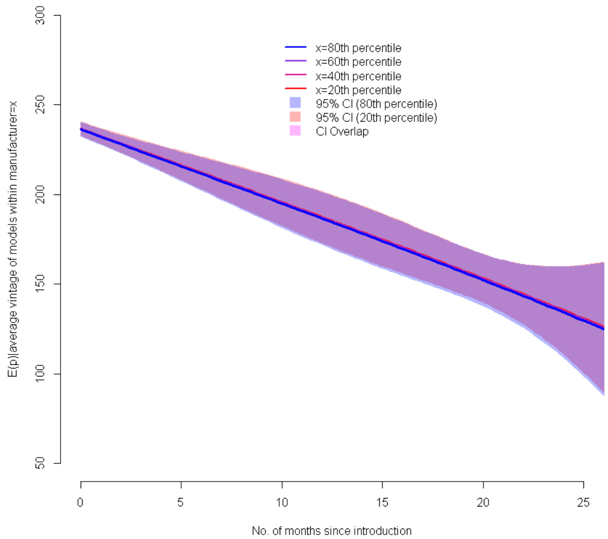


The figure shows the trend in the predicted price of a representative room AC using equation 9 during its first two years. We estimate equation 9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a between-brand average vintage of room AC. The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

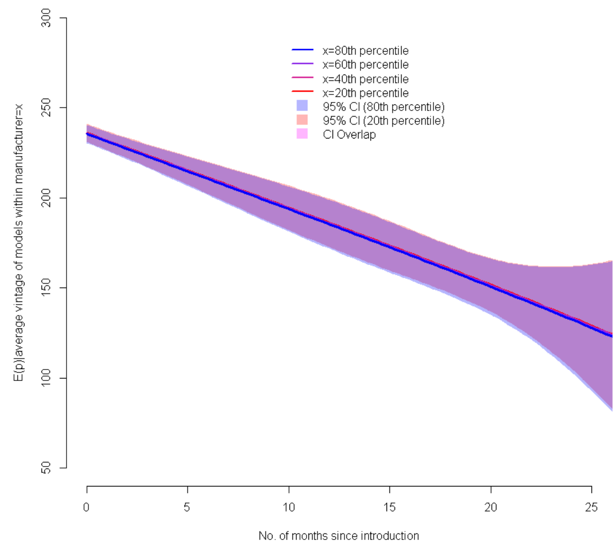
Source: Authors' calculations.

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

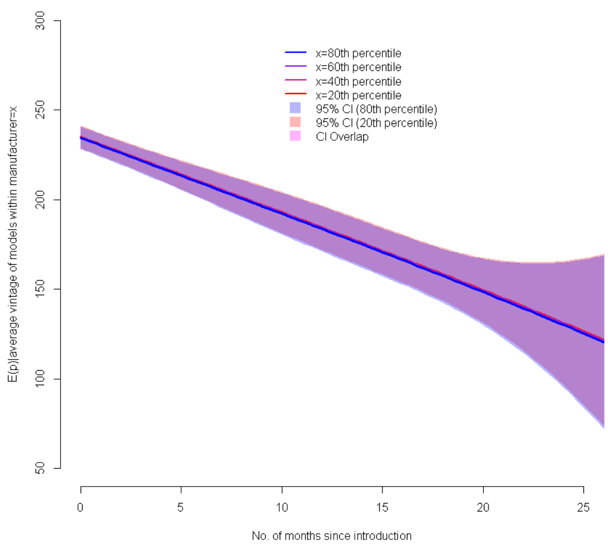
(a) Between Manufacturers Average Vintage = 20^{th} percentile



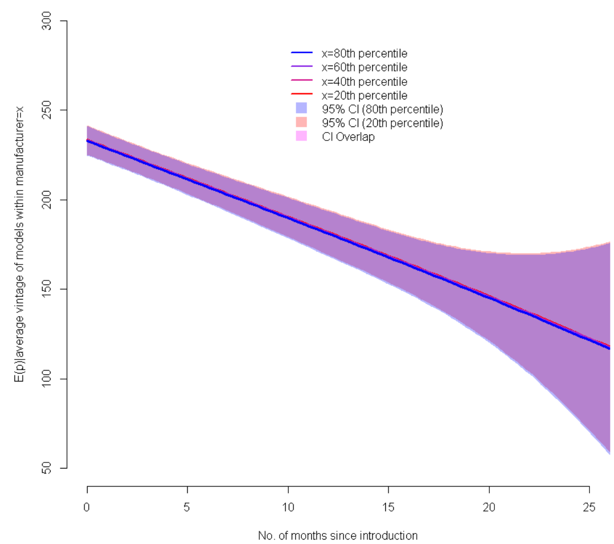
(b)Between Manufacturers Average Vintage = 40^{th} percentile



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



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

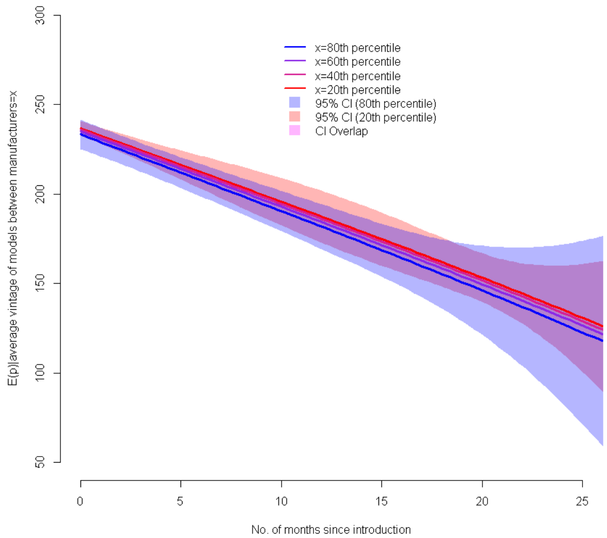


The figure shows the trend in the predicted price of a representative room AC using equation 9 during its first two years. We estimate equation 9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a within-manufacturer average vintage of room AC.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

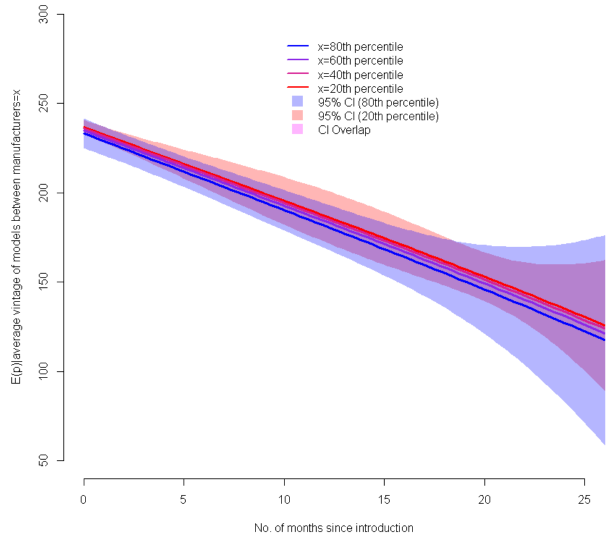
Source: Authors' calculations.

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

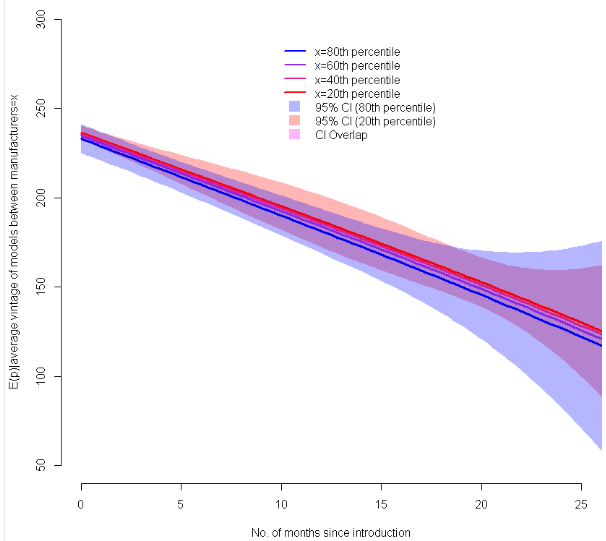
(a) Within Manufacturer Average Vintage = 20^{th} percentile



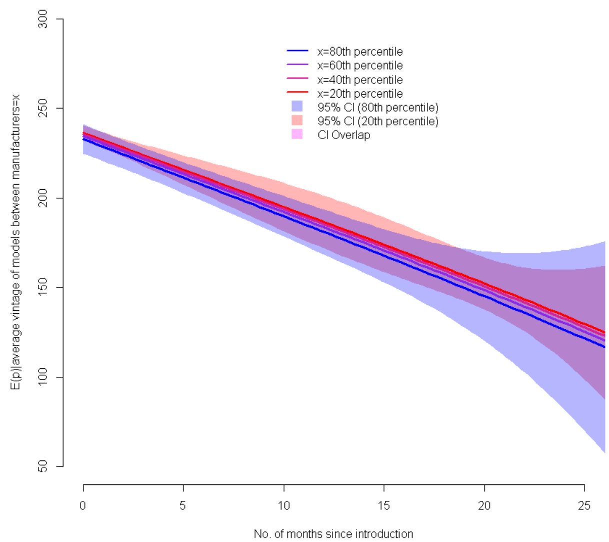
(b) Within Manufacturer Average Vintage = 40^{th} percentile



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



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



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-manufacturers 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-manufacturers average vintage, the 20th, 40th, 60th and 80th percentile correspond to 7.41, 9.08, 11.38, and 14.89, respectively.

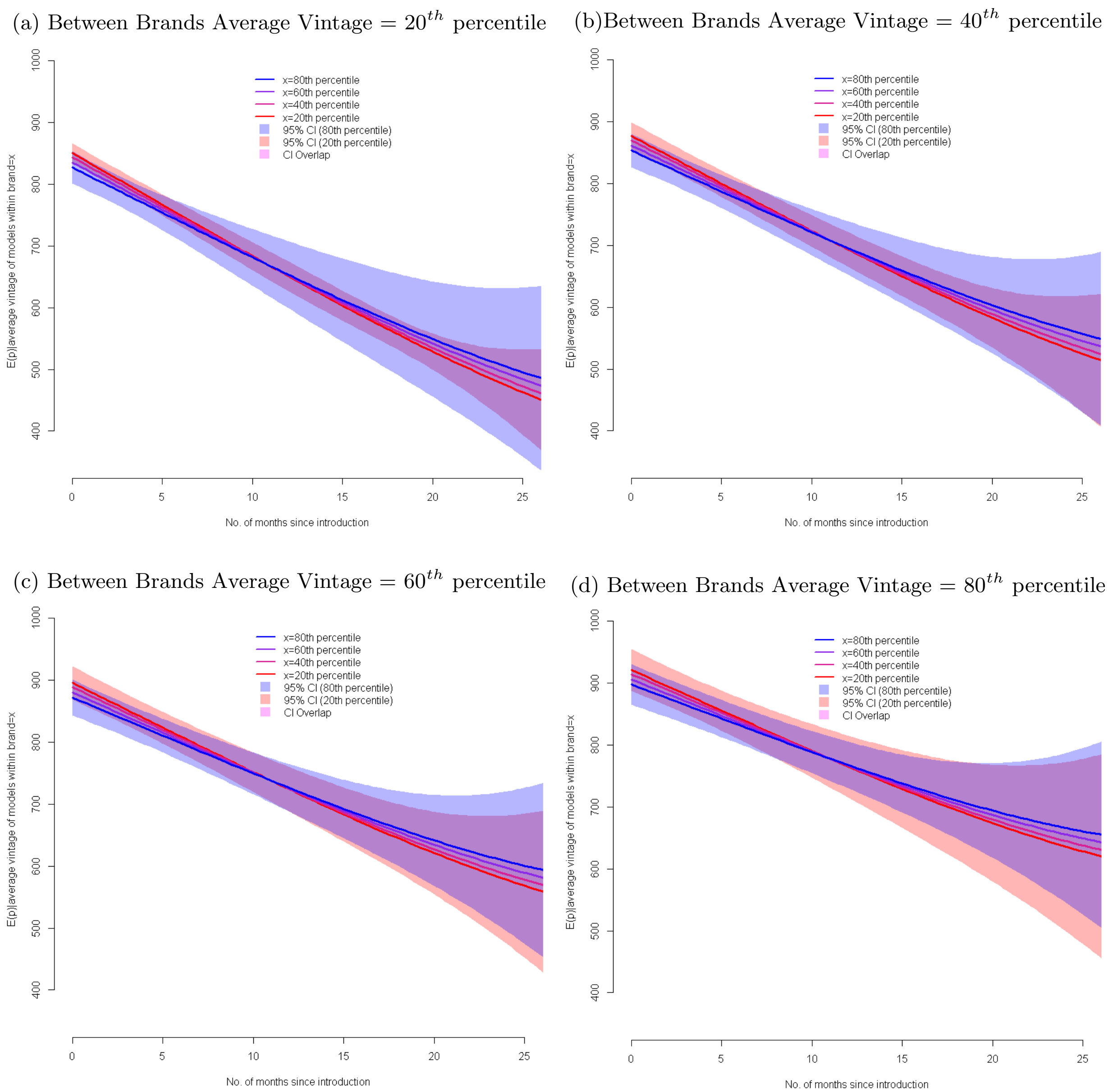
Source: Authors' calculations.

J.C 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 26 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 27 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 refrigerator at different average vintage within the same manufacturer and between manufacturers. Figure 28 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 29 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 26: LIFE CYCLE PRICING OF REFRIGERATORS UNDER DIFFERENT WITHIN-BRANDS AVERAGE VINTAGE

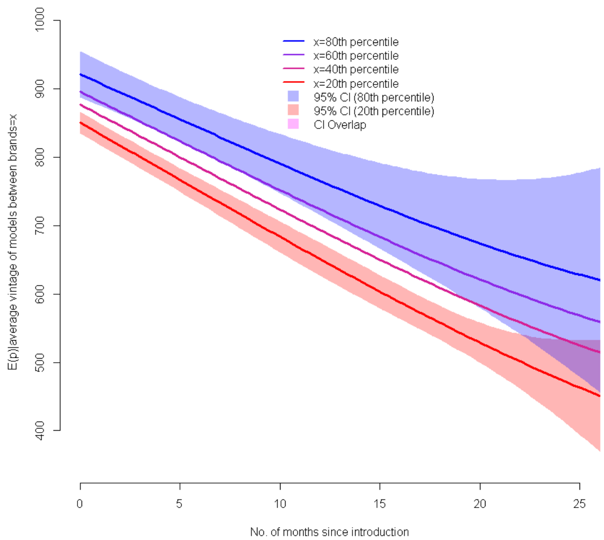


The figure shows the trend in the predicted price of a representative refrigerator using equation 9 during its first two years. We estimate equation 9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a within-brand average vintage of refrigerators.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

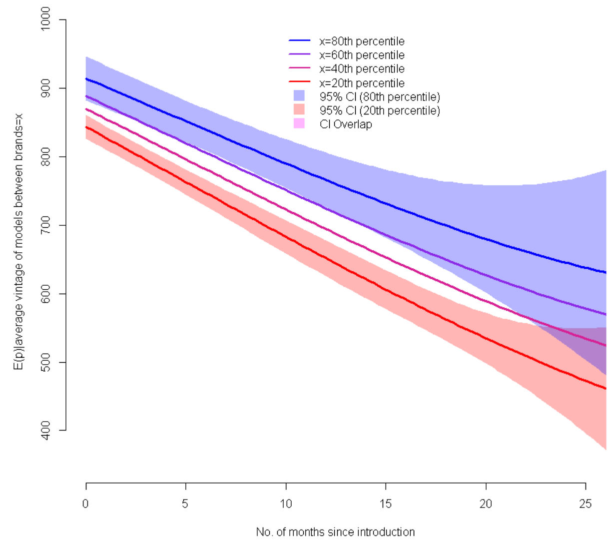
Source: Authors' calculations.

Figure 27: Life Cycle Pricing of Refrigerators Under Different Between-Brands Average Vintage

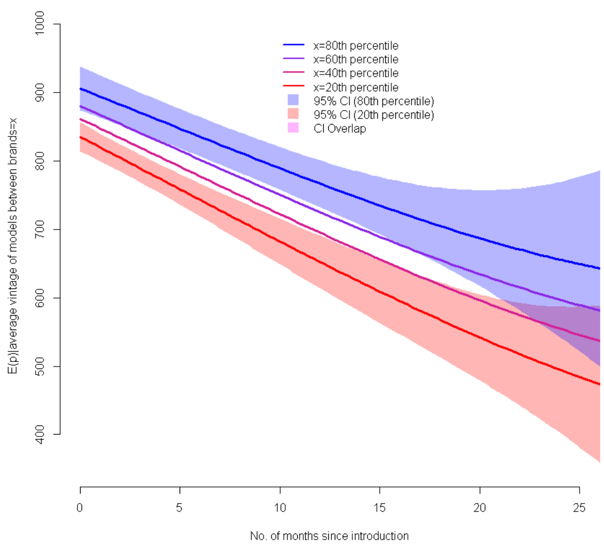
(a) Within Brand Average Vintage = 20^{th} percentile



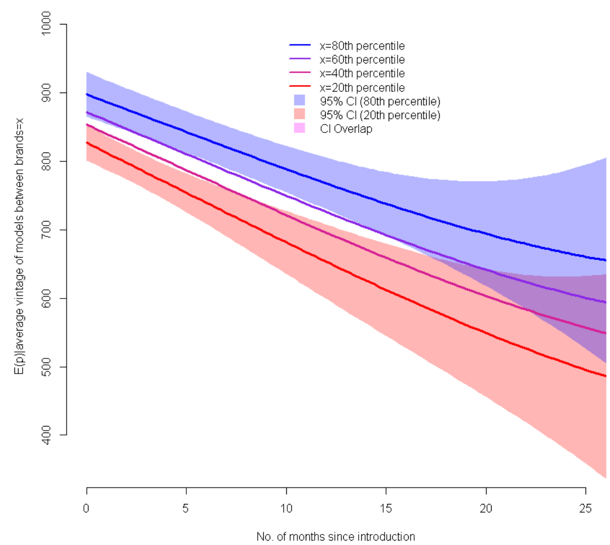
(b)Within Brand Average Vintage = 40^{th} percentile



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



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

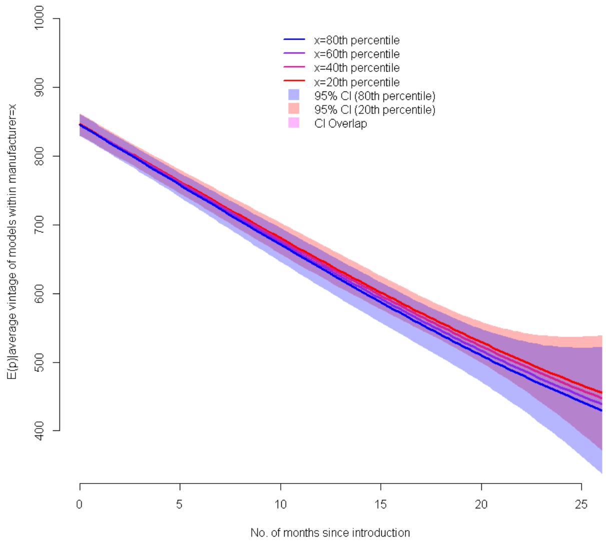


The figure shows the trend in the predicted price of a representative refrigerator using equation 9 during its first two years. We estimate equation 9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a between-brands average vintage of refrigerators. 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.

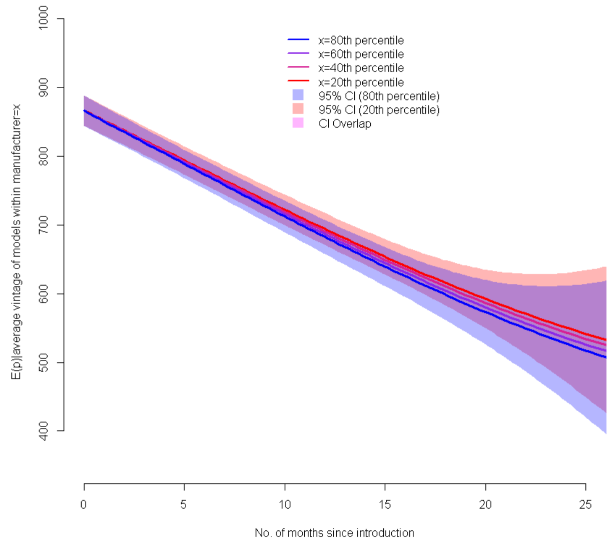
Source: Authors' calculations.

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

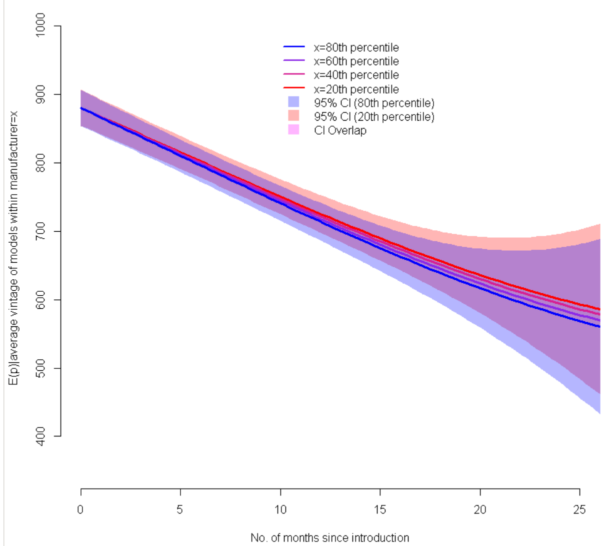
(a) Between Manufacturers Average Vintage = 20^{th} percentile



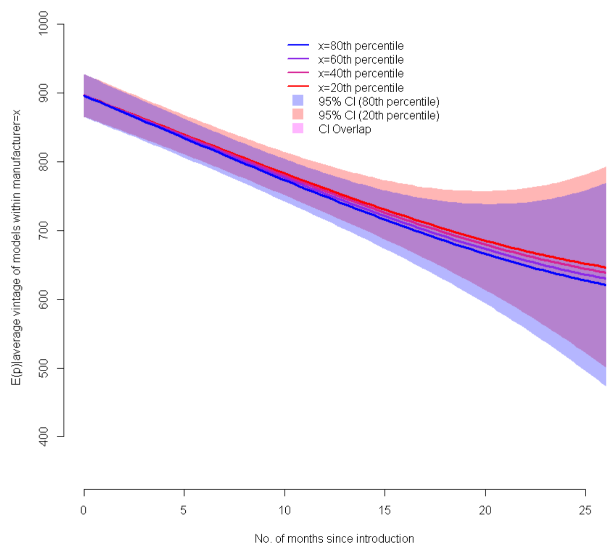
(b)Between Manufacturers Average Vintage = 40^{th} percentile



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



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

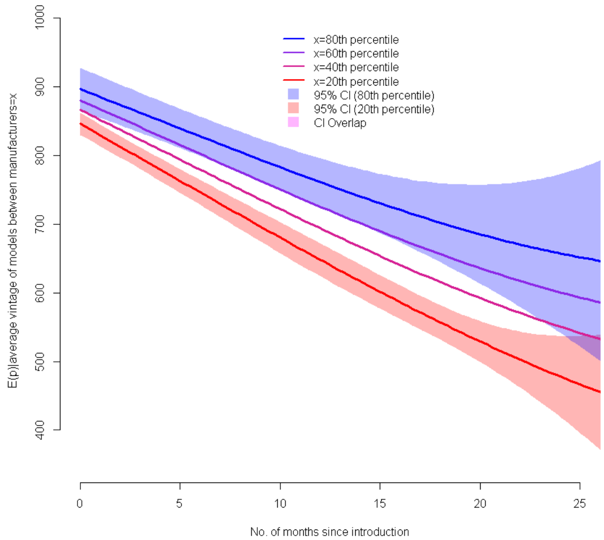


The figure shows the trend in the predicted price of a representative refrigerator using equation 9 during its first two years. We estimate equation 9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a within-manufacturer average vintage of refrigerators.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

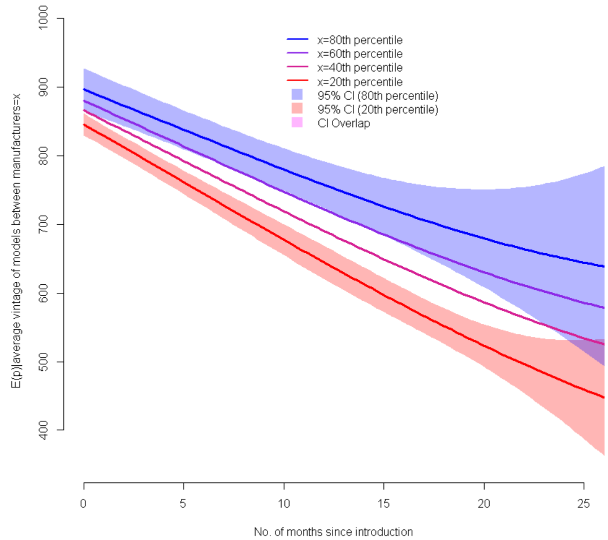
Source: Authors' calculations.

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

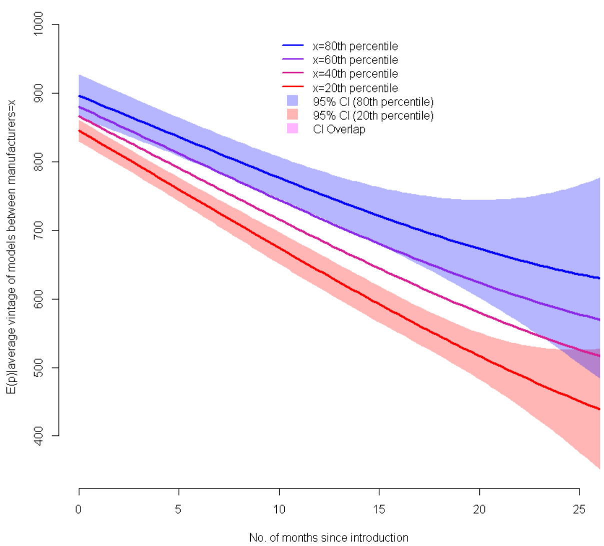
(a) Within Manufacturer Average Vintage = 20^{th} percentile



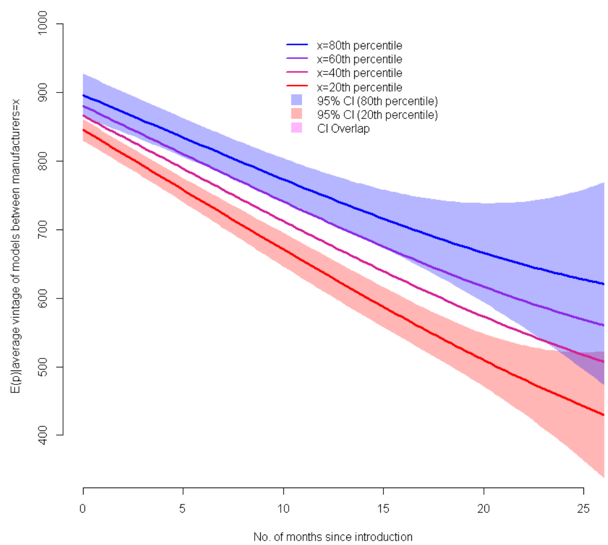
(b) Within Manufacturer Average Vintage = 40^{th} percentile



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



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



The figure shows the trend in the predicted price of a representative refrigerator 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-manufacturers 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-manufacturers average vintage, the 20th, 40th, 60th and 80th percentile correspond to 9.43, 13.13, 15.68, and 18.56, respectively.

Source: Authors' calculations.