

Do Energy Efficiency Standards Hurt Consumers?

Evidence from Household Appliance Sales

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Abstract

We build novel welfare-based price indices for major household appliances that leverage changes in same-model prices and how consumers substitute between exiting, continuing and new models. We then evaluate how minimum energy efficiency requirements and changing criteria for Energy Star labels affected these indices in the U.S. between 2001 and 2011, a period of time when some appliances experienced standard changes while others did not. We find that prices declined while quality and consumer welfare increased, especially when standards become more stringent. We also find that much of the price index decline can be attributed to standards-induced innovation, or cannibalism, not to inter-manufacturer competition. Our results also add to a growing body of evidence that the Consumer Price Index exaggerates inflation due to inadequate account of quality and substitution to new goods.

JEL-Classification: D12, H23, L68, Q48

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1 Introduction

How do energy efficiency standards influence consumer welfare? From a regulatory perspective, consumer welfare implications of standards are important, particularly when these are obscured in engineering-based estimates of costs and benefits. Moreover, the volume of regulated goods as well as the number of countries implementing energy efficiency standards has increased in recent decades, raising the need to better understand benefits and costs, including consumer welfare. Much of the existing literature considers how efficiency standards affect energy savings and pollution externalities, as well as information and behavioral challenges that may interfere with efficient investment in energy saving durable goods purchases (Gillingham et al., 2009; Jaffe et al., 2004). Less research estimates the direct consequences of standards themselves, like how costly they are to consumers and to what extent standards actually reduce energy consumption.

In this paper, we use model-specific data on appliance sales together with methods developed in the trade and price-index literatures (Feenstra, 1994; Broda and Weinstein, 2006, 2010) to evaluate how more stringent energy efficiency standards affected the price and quality of major appliances. We pay particular attention to relatively frequent changes in the minimum energy efficiency standard for clothes washers that occur in our data. We also consider changes the Energy Star[®] thresholds for refrigerators, as well as price indices of room air conditioners (ACs) and clothes dryers, since these appliances did not experience standard changes during the sample period, and thereby serve as controls. Our estimation strategy assesses quality by examining how customers substitute between existing, exiting and new products, similar to Broda and Weinstein (2010), and then examines how different welfare-based price indices respond to differential timing of policy changes across these appliances.

We find no 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 substitution toward new products accelerates with stricter standards. Assuming CES utility and plausible substitution elasticities, the data imply marked improvement in consumer welfare, excluding external pollution-related benefits. Although these results may be surprising to some, a number of theories can explain them. Ronnen (1991) shows how standards can make heterogeneous products more homogeneous, and thereby increase competition, lower prices and improve welfare. Another possibility is that standards facilitate innovation of new products (Jaffe and Palmer, 1997), and improve welfare both through lower prices and increased product diversity, akin to Broda and Weinstein (2010). These ideas recognize that market failures besides pollution externalities and imperfect information may act upon energy efficiency investments, namely imperfect competition and positive externalities of innovation. To investigate these mechanisms, we show evidence that policy-induced changes in price, quality and welfare are associated with entry and exit of models. Specifically, price de-

clines connect more closely to own-manufacturer product introductions (cannibalism) than they do to entry and exit of models by competing manufacturers, a finding that suggests a standard-induced innovation channel rather than a competition channel for price and quality improvements.

A literature on consumers' apparent underinvestment in energy efficient technologies, which may be a key justification of energy efficiency standards, dates back to early hedonic modelling (Hausman, 1979) and consumer choice studies that relate purchase decisions to product prices, energy efficiency, and other product attributes (Train, 1985).¹ Economists typically explain this phenomenon by pointing to market failures, consumer behavioral anomalies and methodological issues.² Most studies, however, do not consider the supply side of the market. Some, however, 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; 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, some studies provide empirical evidence showing the correlation between imposing energy efficiency standards and, like our study, *declining prices* of durable goods (see for example, Greening et al., 1997; Chen et al., 2013; Spurlock, 2013; Spurlock et al., 2013; Van Buskirk et al., 2014; Houde and Spurlock, 2015). Our study, though qualitatively consistent with some of the later studies referenced above, contributes to the literature by: (1) adding additional and, we believe, clearer and more compelling evidence that quality-adjusted prices are unaffected or decline as a result of standard changes; (2) developing novel, appliance-specific, welfare-based price indices that account for same-product prices changes, exit of old (or banned) products, and entry of new products; (3) identifying mechanisms through which energy efficiency standards influence prices, quality, and consumer welfare; and finally (4) providing additional evidence that conventional price indices may exaggerate inflation due to inadequate account of quality and substitution to new goods.

Evidence of causality from standard changes to price and welfare changes is developed using difference-in-difference estimates that exploit asynchronous timing of standard changes for different appliances. The price indices we develop offer a simple and relatively transparent way of calculating consumer welfare, and does not require additional data on consumer characteristics or characteristics of the products they purchase. The approach employs recent developments in price index theory that assumes constant elasticity of substitution (CES) utility together with model-specific data that allow tracking of same-quality products, and accounts for entry and exit based on changes in expenditure shares (Feenstra, 1994; Broda and Weinstein, 2006, 2010; Redding and Weinstein, 2018). It generates results that are similar to those of Houde and Spurlock (2015) who used the

¹The phenomenon has been called the *energy paradox* (Jaffe and Stavins, 1994b) or the *energy efficiency gap* (Jaffe and Stavins, 1994a). Gerarden et al. (2015) distinguish the two by defining the former as a situation where privately optimal energy efficiency investments are not being undertaken while the latter relates to social optimality.

²See (Gerarden et al., 2015) for a review on these issues.

same dataset but estimated a more explicit individual choice model to examine the effect of standards on quality of major appliances sold in the U.S.. To the best of our knowledge, we are the first to explicitly illustrate that most of the changes in product prices in regulated appliances are associated with increased entry and exit of models that occur within the same manufacturer, and not due to increased inter-manufacturer competition.

We briefly review the price index literature, and then show how we develop welfare-based index measures using the expenditure-weighted averages of same-model price changes, both excluding and including new and exiting models. This technique has many applications. 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 (Moulton, 1996; Hausman, 2003). The controversial issue on mismeasurement in the U.S. CPI has a long history. In 1996, the “Boskin Commission Report” estimated that the CPI was overestimated by 1.1 percent per year. The report found that half of the bias resulted from new products and quality changes that were imperfectly accounted for by standard hedonic methods (Boskin et al., 1998). Later, a series of studies emerged providing estimates for the bias that range from insignificant (Greenlees and McClelland, 2011) to two-thirds of price increases (Bils, 2009). More recently Broda and Weinstein (2010), using a database that covers 40-percent of all the expenditure on goods in CPI, find that inflation was between 6 and 9 percentage points lower than indicated by the CPI between 1994-2003. Analysis by Redding and Weinstein (2018) indicates larger bias. The indices we develop provide a simple way to accurately measure price changes by considering only continuing appliance models that were sold across multiple periods, thus holding quality constant during the period. This index is then adjusted for entry and exit of models based on expenditure shares and assumed or estimated elasticities of substitution. Consistent with Broda and Weinstein (2010) and Redding and Weinstein (2018), we find that prices for laundry equipment (clothes washers and dryers) for the period 2002-2011 fell about 3 percentage points more than the CPI for laundry equipment.

The rest of the paper is organized as follows. Section 2 provides a overview of energy efficiency standards covered in this study. Section 3 reviews the price index literature, recent developments, and how we adapt this literature for our own analysis of energy-consuming durable goods. Section 4 describes the data and section 5 describes methods and estimates of the elasticity of substitution. Section 6 presents estimates of impacts from standards using differences and differences-in-differences. Section 7 presents further evidence on the degree to which price reductions of older continuing models are induced by introductions of new products by both same and competing brands and manufacturers. Section 8 discusses a range of implications of the empirical results and concludes.

2 Energy Efficiency Standards

The appliances we study—clothes washers and dryers, refrigerators and room air conditioners—are among those subject to either federal minimum energy (ME) and Energy Star[®] (ES) standards. ME standards began with the passage of the National Appliance Energy Conservation Act (NAECA) in 1987. The law established an initial minimum energy efficiency standard for a set of appliances sold in the U.S. and directed the Department of Energy (DOE) to periodically update them. Subsequent legislation, such as the Energy Policy Act of 1992, the Energy Policy Act of 2005, and the Energy Independence and Security Act 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.

To ensure implementation of standards the DOE publishes certification, compliance and enforcement regulation. These regulations prescribe test procedures to establish certified energy efficiency ratings and require manufacturers to submit certification reports to DOE. An appliance must comply with standards in place on its manufacturing date or the date the appliance was imported for sale in the U.S. Thus, appliances manufactured or imported before the effective date of a new ME standard can still be sold in the U.S. market.

Although DOE has 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 consideration 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 as the discounted value of energy-related savings. A common complaint from the Office of Management and Budget 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 have less desirable performance characteristics as compared to the less efficient appliances that they replace. By their nature, some 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 U.S. government sets thresholds for ES qualification. ES is a voluntary program that identifies and promotes energy efficiency by labelling products that meet higher efficiency requirements set forth by the Environmental Protection Agency (EPA). DOE periodically revises the federal minimum energy efficiency thresholds based on judgment about available technologies. EPA typically revises the ES threshold when ES comprises 50 percent or

higher share of sales. Thus, the timing of ES changes may not coincide with changes in the minimum energy efficiency standards, although minimum standards also factor into decisions to revise ES qualification.

To investigate impacts of standard changes, we leverage differential timing of ME and ES standard changes across major appliances. 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. No ME or ES standards changed for clothes dryers and room air conditioners between 2001 and 2011.

Table 1: U.S. 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 types of clothes washers and refrigerators.

Source: Department of Energy

3 Price, Quality and Welfare Measures

To examine how appliance prices and qualities change over time, we draw on recent innovations in the price index literature, normally used to track changes in the general cost of living, like the consumer price index (CPI). More recently, price indices have taken advantage of universal product code (UPC) data to track prices of exact products over time, data that can be used to better

account for quality changes and changing varieties, which can be inferred by observing substitution from exiting and continuing products to new products (Feenstra, 1994; Broda and Weinstein, 2006, 2010). We take a similar approach in this paper, except we focus on appliances for which product entry and exit have been influenced by changing energy efficiency standards. By observing how both prices and purchase shares of new versus continuing models change, we infer changes in consumer welfare.

3.A Price Indices

Development of standard price indices draws on the expenditure function $e(p, u_0)$, which gives the minimum cost of attaining a fixed level of utility (u_0) for a given vector of prices p . If prices change from p_0 to p_1 , an ideal price index is $P = \frac{e(p_1, u_0)}{e(p_0, u_0)}$, for it gives the proportional change in income needed to maintain the same standard of living. The expenditure function subsumes preferences and choices that adjust as relative prices change and new products are introduced. Without making assumptions about the shape of the utility function, we can bound the price index by holding quantities fixed instead of utility. Fixing quantities at the initial period (the Laspeyres index) overestimates the change in the cost of living, for it assumes zero substitution; fixing quantities in the second period (the Paasch index) underestimates the change. Splitting the difference and weighting prices by average quantity of the two periods seems like a sensible compromise, which gives the Marshall-Edgeworth index; similarly, the Fisher index is the geometric average of the Laspeyres and Paasche indices (Diewert, 1988).

A utility function is needed to calculate an index that reflects a precise change in welfare. An elegant solution comes from assuming constant elasticity of substitution (CES). Regardless of the product share and elasticity parameters, Sato (1976) and Vartia (1976) show that CES utility implies an exact price index that equals the weighted geometric mean of individual product price ratios:³

$$P_t = \prod_i \left(\frac{p_{i,t}}{p_{i,t-1}} \right)^{w_{i,t}} \quad (1)$$

where the weights $w_{i,t}$ are calculated using expenditure shares as follows,

³Also see Feenstra (1994).

$$s_{i,t} \equiv \frac{p_{i,t}x_{i,t}}{\sum_i p_{i,t}x_{i,t}} \quad (2)$$

$$w_{i,t} \equiv \frac{\frac{s_{i,t}-s_{i,t-1}}{\ln s_{i,t}-\ln s_{i,t-1}}}{\sum_i \left(\frac{s_{i,t}-s_{i,t-1}}{\ln s_{i,t}-\ln s_{i,t-1}} \right)}. \quad (3)$$

CES utility may or may not be a reasonable approximation of preferences, as it assumes the same degree of substitutability between all goods. And while CES utility can represent aggregate demand of a heterogeneous constituent population of individuals ([Anderson et al., 1992](#)), it is nonetheless restrictive.

Another key issue concerns the definitions and measures of individual goods that enter the index. Product quality of individual goods can change over time, new goods can be introduced, and some old goods exit. Traditionally, hedonic methods have been used to adjust prices of individual goods for changes in characteristics, and thereby account for quality. With the growth of large digitized data sets, quantities and prices of unique individual products can be tracked. When quantities and prices are measured by UPC or product-specific model number (like we do here), quality is arguably fixed, and broader quality changes can be discerned by how consumers substitute between continuing goods and new goods. [Feenstra \(1994\)](#) extends the CES-based index to account for new goods, and [Broda and Weinstein \(2006\)](#) and [Redding and Weinstein \(2018\)](#) apply this method to product-specific UPC data, methods that we now adopt in this paper.⁴

To simplify notation, we follow [Broda and Weinstein](#) and define *common goods* as continuing goods, i.e., those appearing in both periods t and $t - 1$. A chained index is developed by defining a new set of common goods for every time difference, such that the base year is reset to period $t - 1$ for each period t . Define the CES price index for common goods only as P_t^* . This index is calculated like equation 4 except it excludes goods that exit between periods t and $t - 1$ and goods that enter in period t . [Feenstra \(1994\)](#) shows that the CES-based index inclusive of new and exiting goods is

⁴In an earlier version of this paper, we developed a price index that was similar in concept, but not tied to an explicit utility function. Instead of inferring welfare improvement by the expenditure share of new goods verses exiting goods, we inferred welfare improvement non-parametrically by substitution from a constant-quality index of continuing goods and all goods, as reflected by average price. The results are very similar.

$$P_t^\sigma = P_t^* \left(\frac{\lambda_t}{\lambda_{t-1}} \right)^{\frac{1}{\sigma-1}} \quad (4)$$

where σ is the elasticity of substitution, λ_t is the common goods share of total sales in period t , and λ_{t-1} is the common goods share of sales in $t-1$.⁵ Holding the common goods price index constant, if this ratio of shares is less than one, it implies that as goods exited, consumers spent more on new goods than they did on exiting goods, implying a welfare improvement. Conversely, if the ratio is greater than one, then consumers substituted more toward common goods than new goods, resulting in a welfare decline. With entry and exit of goods, the exact price index now depends on σ , which must be estimated, an issue we address below. The larger the elasticity of substitution, the closer P^σ will be to P^* .

3.B Price Indices for Appliances

Using model-specific prices and quantities, we develop indices akin to those described above. The only difference is that these indices are calculated for specific products (e.g., washing machines) rather than a broad basket of consumer goods. Specifically, we develop four price indices: a Marshall-Edwards index with equal weighting of sequential periods (P^{ME}), a Fisher index that equals the geometric average of Laspeyres and Paache (P^F) indices, a CES-based exact index based on common goods only (P^*), and a full CES-based index inclusive of model entry and exit, which we denote with (P^σ), where σ is the elasticity of substitution.⁶ Note that in all cases we develop chained indices that recalculate the set of common goods and base year every two periods, and all indices except the full CES index (P^σ) exclude new and exiting models.

It is worth noting that the assumption of CES utility for products within a product group may be more realistic than assuming CES across all products. CES assumes all goods are gross substitutes, independence of irrelevant alternatives, and the same elasticity of substitution between all products. These assumptions seem more plausible for consumers deciding between a Whirlpool, GE or Samsung refrigerator, but less plausible when considering allocation of a budget between appliances, food, and recreation activities; or worse, durable goods and energy, which may be complements. We might also expect the elasticity of substitution to be larger than an elasticity

⁵Note that λ_{t-1} is not simply the lag of λ_t , since the definition of common goods changes for each pair of sequential time periods.

⁶In an earlier version of this paper we developed an index using price changes measured as a percent of average price in two sequential periods, weighted by the average quantity sold in the two periods. This index is similar in concept to Marshall-Edwards and Fisher, is nearly indistinguishable from these indices, and happens to lie between them. We dropped the index for simplicity and continuity with the previous literature.

used for all goods or for broad categories of goods, since different washing machines with different features, brands or sizes are surely more substitutable than appliances and coffee (for example).

Still, the full CES index P with entry and exit requires an elasticity of substitution. One option is to simply assume an elasticity, conservatively estimated as being similar to those estimated for broader classes of goods. A second option is to estimate elasticities using the identification strategy suggested by [Feenstra \(1994\)](#). We do both. In the next section we describe the data used to construct the price indices. In the subsequent section we describe the identification strategy for estimating σ and report estimates, which turn out to be considerably larger than 10, which is the benchmark elasticity that we assume.

One problem with product-specific indices is that each one comprises a small share of consumption expenditures. Because consumers can substitute between these appliances and other products, product-specific indices underestimate welfare gains. In effect, the estimates assume perfectly inelastic demand for the product group, only accounting for substitution between individual appliance models, not substitution between appliances and other goods. Thus, conditional on an assumed elasticity of demand for the whole product group relative to other goods, one can also approximate the size of additional welfare gains. Otherwise, we underestimate the welfare gains in the event that the price index declines, and exaggerate the welfare loss if the price index increases.

4 Data and Appliance Price Indices

Point-of-sale data for clothes washers, clothes dryers, room air conditioners, and refrigerators were obtained from the NPD Group, purchased by Lawrence Berkeley National Laboratory. The data were collected from a set of U.S. retailers (both online and in-store) and are aggregated at the national level.⁷ On average, the data represents about 32% of the total shipments of clothes washers sold in the United States from 2002-2011, while dryers, refrigerators and room air conditioners account for 32%, 35% and 25%, respectively. In terms of revenue the data represents about 37% of the industry total for washers and dryers, and 36% for refrigerators and room air conditioners. A list of participating retailers and the share of appliances in our sample to total U.S. market and total shipments are provided in [Appendix A](#) and [Appendix B](#), respectively.

The data include monthly total revenue and total quantity sold by individual model number from January 2001 to December 2011. Each model number uniquely characterizes each product, including its specific color. We therefore believe it reasonable to treat these identification numbers in the same way [Broda and Weinstein \(2006\)](#), [Broda and Weinstein \(2010\)](#), and [Redding and Weinstein \(2018\)](#) treat UPC codes: as fixed products with unchanging quality over

⁷NPD group was unable to provide subnational aggregations.

time. We calculate the unit price of each model by dividing total revenue by total units sold in each month. This price includes in-store discounts for individual models of appliances, but not mail-in rebates. To check how this price variable represents actual sales price, we randomly selected 30 models of clothes 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 air conditioners, 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. For example, Kenmore is a brand of appliance that is sold exclusively by Sears, such that unmasked models would indicate sales of the particular retailer. Refrigerators and room air conditioners 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 F.](#))⁸ Summary statistics are reported in [Table 2.](#)

In [Figures 1 and 2](#), we plot average prices of each appliance and each of the price indices, respectively. While average prices are generally flat, all of the price indices, which hold quality constant or account for new products, show falling prices and improving welfare ([Figure 2](#)). For all appliances, the proportional change in expenditure share on common goods ($\frac{\lambda_t}{\lambda_{t-1}}$) is typically less than one, indicating an improvement in welfare from introductions of new models, and this falls quite sharply with major introductions of new appliances ([Figure 3](#)). As a result, indices that account for entry and exit of models sit below the CES common goods index, and the lower the elasticity, the more the indices fall and the greater the implied welfare improvement.

The largest single change in minimum energy efficiency standards was for washing machines in 2004. This event coincides with a large change in the expenditure share of common goods, and a decline in the price index. The common goods index P^* declined slightly over this time frame, while the proportional change in expenditure share on common goods was less than one. The welfare improvement is modest under the estimated elasticity, however, because it is so large.

⁸A substantial share of masked models may come from Sears-specific models, a notable retailer whose share of the appliance market declined considerably during our sample period and since. The decline of Sears may influence competition and product variety with a detrimental influence on consumers. The merger between Whirlpool and Maytag may have had similar influence ([Ashenfelter et al., 2013](#)). The robustness of our results to including or excluding masked models suggests this is not an significant issue in our sample. A compensating differential may be entry and growth of new manufacturers, particularly Samsung and LG.

Table 2: SUMMARY STATISTICS

	Washer		Refrigerator		Room Air Conditioner	
	Baseline (1)	No Masked (2)	Baseline (1)	No Masked (2)	Baseline (1)	No Masked (2)
Price (\$)	650.55 (355.92)	700.09 (348.89)	1,378.75 (1,383.51)	1,464.47 (1,355.75)	332.53 (240.27)	337.18 (215.76)
Sales (units)	744.00 (1,908.47)	872.30 (2,007.55)	199.61 (736.51)	203.68 (617.18)	590.72 (3,264.15)	757.67 (3,025.81)
Revenue ('000\$)	382.40 (966.37)	481.45 (111.02)	143.15 (451.36)	167.16 (468.18)	119.11 (581.32)	147.71 (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 monthly average price, sales and revenues generated between 2001 and 2011 for each of the following: (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 U.S.\$.

Source: The NPD Group

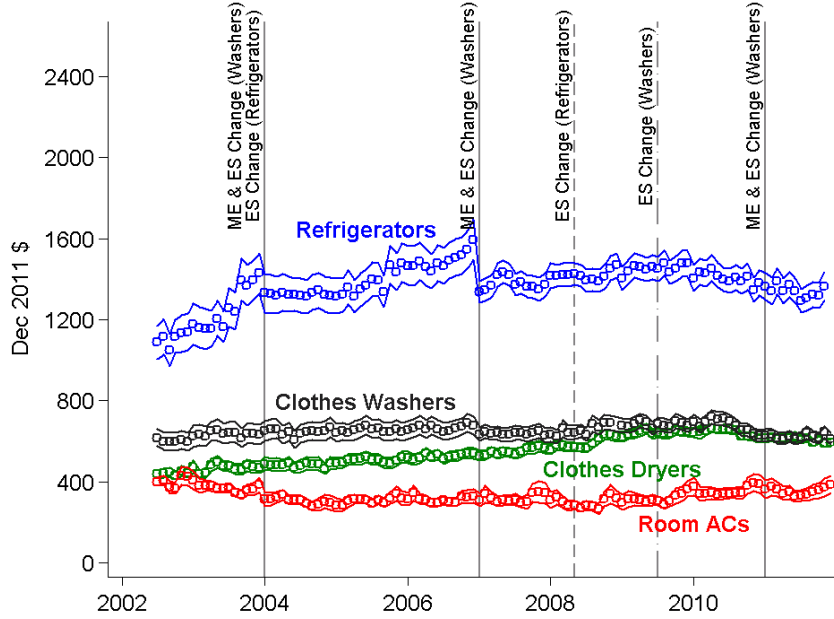
If the elasticity of substitution is smaller, the welfare gain is considerably greater. There is no indication that the change in standards hurt consumers.

One interesting anomaly is the rise in price indices around 2005. We see this anomaly in all three appliances and it is especially large for air conditioners, which did not have any changes in efficiency standards or Energy Star thresholds. It therefore seems unlikely that this is a delayed or anticipatory response to a policy change. We speculate that this anomaly may have something to do with the housing bubble; it is around the time that housing starts peaked.

5 Estimating an Elasticity of Substitution

To estimate an elasticity of substitution for each appliance group, we employ the method developed by Feenstra (1994), which draws on insights by Leamer (1981). Leamer shows that, while supply and demand elasticities cannot be identified with price and quantity data alone (i.e., without instruments), one can put bounds on supply and demand elasticities, which must lie on a hyperbola defined by the regression coefficient of quantity on price (and vice versa), and the error variances. With many products and a single elasticity summarizing substitution between products, as in CES, and further assuming that all appliance models have the same supply elasticity, we can identify both parameters by making assumptions about the correlation of supply and demand shocks associated with individual appliances. Specifically, we must assume that after double differencing (subtracting mean price and expenditure shares from individual product shares, and then differencing over time),

Figure 1: AVERAGE PRICE, CLOTHES WASHERS, REFRIGERATORS, ROOM ACS AND CLOTHES DRYERS, 2002,2011



Notes: The figure shows sales-weighted average prices and 95 percent confidence bands for each appliance across time. The solid 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 U.S. dollars.

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

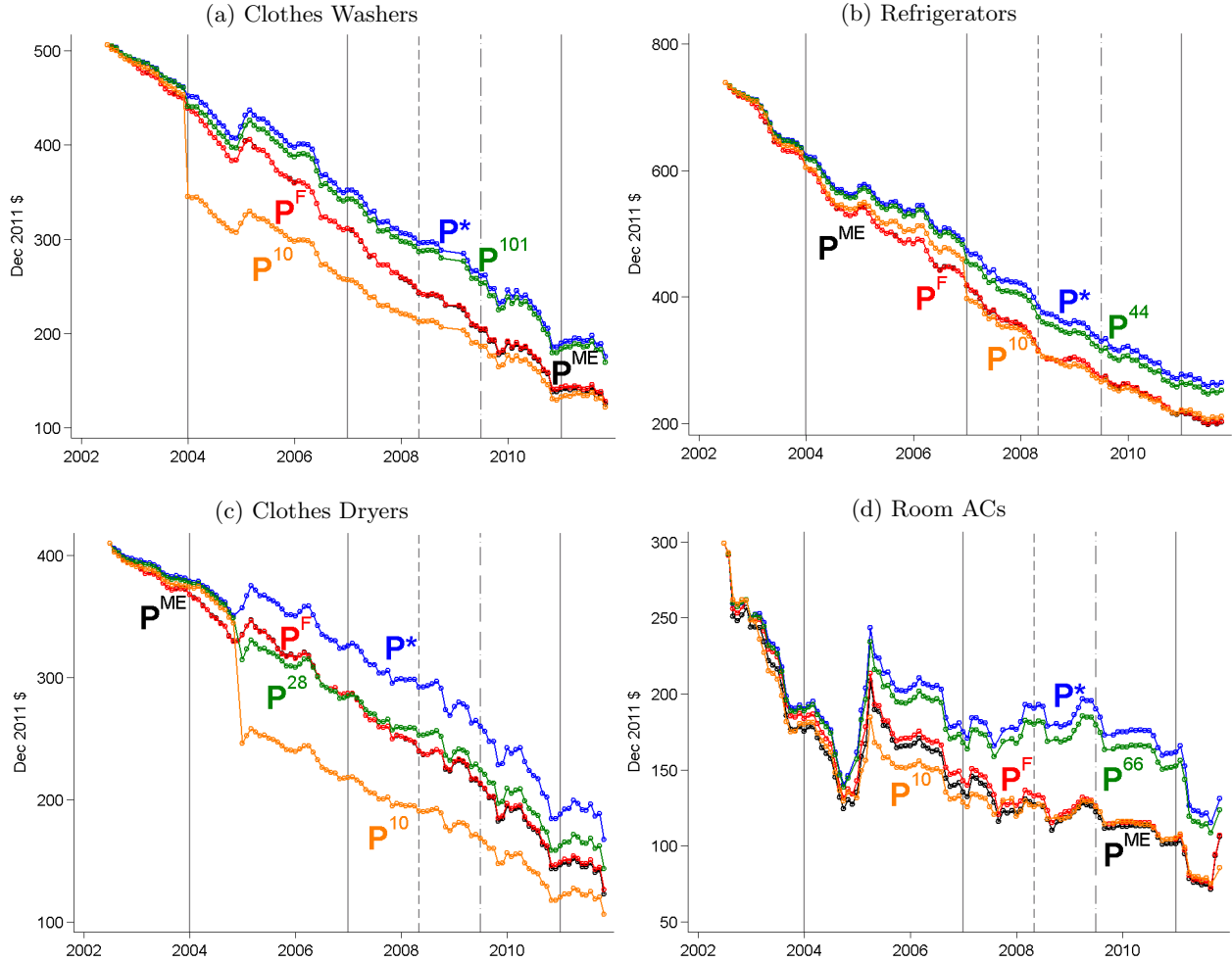
supply shocks (unobserved changes in costs) are not correlated with demand shocks (unobserved changes in preferences). Identification also requires the error variances of the supply and demand shocks for the different individual products to differ, thereby identifying many hyperbolas, the intersection of which identifies the elasticities.

These assumptions allow us to identify supply and demand elasticities using weighted least squares. These methods were extended by [Broda and Weinstein \(2006\)](#), [Broda and Weinstein \(2010\)](#), and [Redding and Weinstein \(2018\)](#). Following [Feenstra \(1994\)](#), we spell out the mechanics of estimation; readers are directed to the above references for a formal derivation.

Define $y_{i,t}$ and $x_{1,t}$ as the variance of prices and shares, respectively, given by the following:

$$y_{i,t} = (\Delta \ln p_{i,t} - \Delta \ln p_{k,t})^2 \quad (5)$$

Figure 2: PRICE INDICES, CLOTHES WASHERS, REFRIGERATORS, ROOM ACs AND CLOTHES DRYERS, 2002-2011



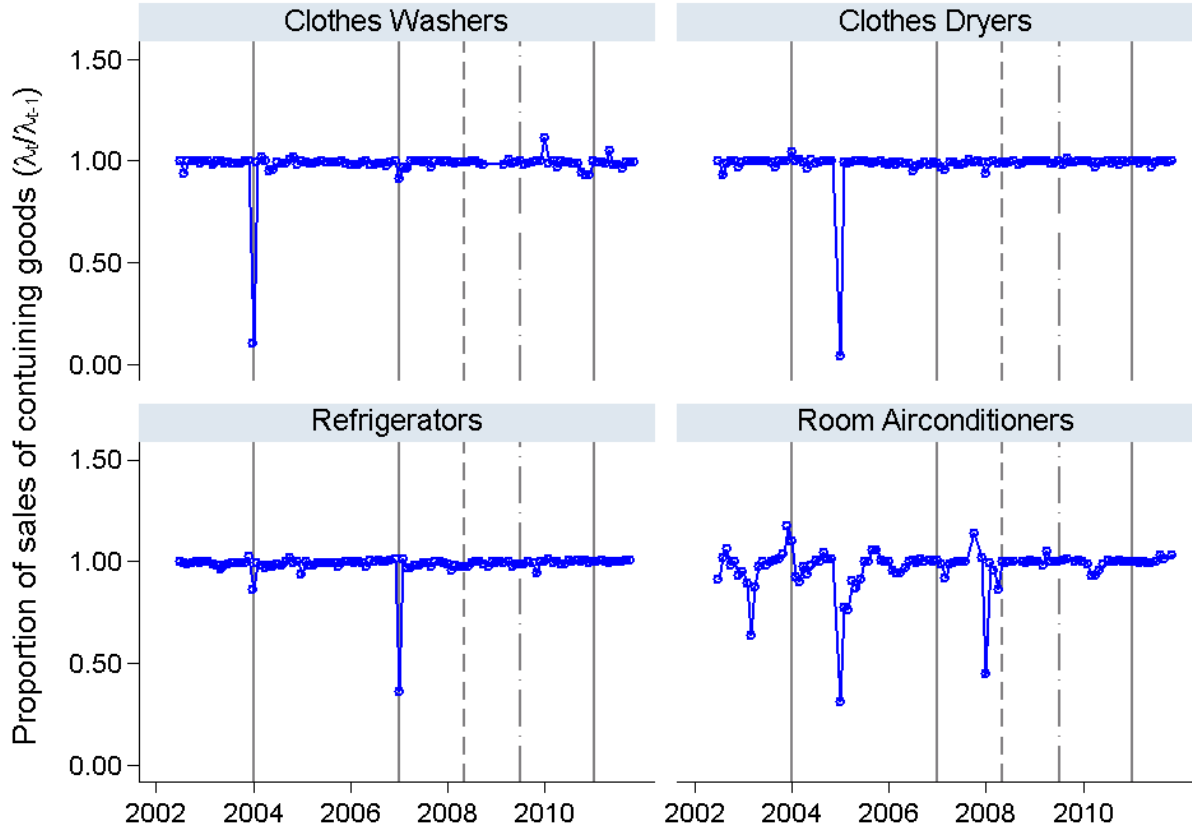
Notes: Panels (a)-(d) show the calculated price indices for clothes washers, refrigerators, and room ACs, respectively. P^{ME} and P^F are the Marshall-Edgeworth and Fisher price indices, respectively; P^* is the CES-based index for common goods; $P^{\hat{\sigma}}$ is the CES-based index with new and exiting models and the estimated elasticity of substitution (101 for washers; 44 for refrigerators, and 66 for room air conditioners); and P^{10} is the CES-based index with a substitution elasticity of 10. The solid 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 U.S. dollars.

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

$$x_{1,i,t} = (\Delta \ln s_{i,t} - \Delta \ln s_{k,t})^2 \quad (6)$$

where $\Delta p_{i,t}$ is the change in price of continuing model i from period $t - 1$ to period t , $\Delta p_{k,t}$ is the geometric average price change of common goods in period t , $\Delta \ln s_{i,t}$ is the change in expenditure

Figure 3: RATIO OF CONTINUING MODELS BETWEEN t AND $t - 1$.



Notes: The figure shows the expenditure share on continuing models between periods t and $t - 1$, $(\frac{\lambda_t}{\lambda_{t-1}})$. The solid vertical lines represent the effective date of simultaneous policy changes in the federal minimum energy standard and Energy Star certification threshold, while the dashed line is for the Energy Star efficiency 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).

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

share of continuing good i in period t , and $\Delta \ln s_{k,t}$ is the geometric average expenditure share of continuing goods.

We also define $x_{2i,t}$ as their covariance given by

$$x_{2i,t} = (\Delta \ln s_{i,t} - \Delta \ln s_{k,t}) (\Delta \ln p_{i,t} - \Delta \ln p_{k,t}) \quad (7)$$

Further define \bar{y}_i , \bar{x}_1_i , \bar{x}_2_i as the sample means over non-missing time periods for each model

i .⁹ The estimating equation is:

$$\bar{y}_i = \theta_1 \bar{x}_{1i} + \theta_2 \bar{x}_{2i} + u_i, \quad (8)$$

which we estimate using weighted least squares, the weights equal to the sum of units sold of model i . Equation 8 is Feenstra (1994)'s estimator, which minimizes the distance between the hyperbolas across different models in the sample. According to Feenstra (1994), this estimation method is equivalent to 2SLS procedure which begins with the mapping of each model's hyperbola to a single observation defined by its variance of prices (\bar{y}_i) and shares (\bar{x}_{1i}) along with its price and share covariance (\bar{x}_{2i}), and then followed by fitting a line through these points by regressing \bar{y}_i on \bar{x}_{1i} and \bar{x}_{2i} (Soderbery, 2015).

The estimated elasticities are implied by $\hat{\theta}_1$ and $\hat{\theta}_2$ (see Proposition 2 in Feenstra (1994)). If we define $\hat{\rho}$ as the estimate of the common supply elasticity and $\hat{\sigma}$ as the elasticity of substitution, these are given by

if $\hat{\theta}_2 > 0$ then

$$\hat{\rho} = \frac{1}{2} + \left(\frac{1}{4} - \frac{1}{4 + (\hat{\theta}_2^2 / \hat{\theta}_1)} \right)^{1/2} \quad (9)$$

if $\hat{\theta}_2 < 0$ then

$$\hat{\rho} = \frac{1}{2} - \left(\frac{1}{4} - \frac{1}{4 + (\hat{\theta}_2^2 / \hat{\theta}_1)} \right)^{1/2} \quad (10)$$

and in either case:

$$\hat{\sigma} = 1 - \left(\frac{2\hat{\rho} - 1}{1 - \hat{\rho}} \right) \frac{1}{\hat{\theta}_2} \quad (11)$$

Note that σ must be greater than 1, and if $\hat{\theta}_1$ is negative, the above formulas do not provide valid estimates of ρ and σ .

One concern with using this method is that estimation makes use of common goods that appear in each time difference, excluding new and exiting goods. If the elasticity of substitution

⁹Averaging over time periods helps to resolve a fundamental endogeneity and makes the estimator consistent for large T . The data possess considerably more models than time periods per model, so there is likely some degree of bias in our estimates, which is another reason we consider implications of a smaller elasticity.

between new models and all other models differs considerably from the others (for example, some consumers possess a strong preference for new models), the elasticity of substitution may be biased upward.¹⁰ This is another reason we consider the implications of a smaller elasticity (i.e., $\sigma = 10$).

Results of estimating equation 8 and the implied demand and supply elasticity estimates (equations 9 - 11) are presented in Table 3. The estimated elasticities appear high for all appliances, ranging from about 28 to 102. On the one hand, high elasticities make sense, given they account for substitution between very similar products. On the other hand, these estimates may be biased too high, for the reasons described above. Recall that as σ approaches infinity, P^σ approaches P^* . The implication is that the estimated elasticities give an upper bound on the price level and underestimate implied consumer welfare improvement.

Table 3: Estimates of Substitution Elasticities

Parameter Estimates	Clothes Washers	Clothes Dryers	Refrigerators	Room ACs
θ_1	0.002 (0.002)	0.011** (0.004)	0.005 (0.004)	0.003 (0.003)
θ_2	0.212*** (0.050)	0.254*** (0.035)	0.187** (0.090)	0.176** (0.049)
R-sq.	0.285	0.352	0.558	0.315
Observations	1,837	2,928	9,187	2,098
$\hat{\rho}$	0.96	0.25	0.90	0.93
$\hat{\sigma}$	101.7	27.7	43.9	65.9

This table reports estimates of equation 8 and the implied demand and supply elasticity estimates (equations 9 - 11). Robust standard errors are in parentheses. *, **, *** denote statistical significance at 10, 5 and 1 percent, respectively.

6 Effects of Standard Changes on Prices Indices and Welfare

In this section we examine whether the price indices, both adjusted and unadjusted for entry and exit of models, have been affected by changes in minimum energy efficiency and Energy Star standards. We estimate effects of standard changes using differences (pre/post) and difference-in-differences comparisons.

The differences analysis considers each appliance separately, and we simply report mean price index changes in each window before, during and after a policy change. Because policy changes were

¹⁰When applied to U.S. import data from 1993 to 2007, Soderbery (2015) has shown that median demand and supply estimates derived from Feenstra (1994)'s method were overestimated by over 35%, thus reducing consumer gains from product variety by a factor of 6.

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. To the extent feasible, we compare the changes within the policy change period to those in one year prior and one year after the policy change 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. Effectively, we compare price changes on a year-on-year basis. Using a shorter, say 3-month policy window, might capture price changes that are associated with seasonal variations in demand and supply, and results can be stronger. If we make the window much larger, controls begin to vanish. Table 4 gives the results.

The results show accelerated price declines around policy changes relative to previous and succeeding periods. For example, the average monthly drop in P^* for clothes washers around the 2004 ME and ES policy change was about 1.11 percentage points per period, compared to 0.65 and 0.36 percentage point before and after the policy period, respectively. During this change, which was arguably the most substantial policy change in our data, the ratio $(\lambda_t/\lambda_{t-1})$, which gives the share of expenditures on common goods in the current period relative to the previous period, is by far the lowest observed, 0.916. A ratio less than one implies substitution to the new models introduced during this period, and a larger welfare improvement than implied by the decline in P^* . This improvement carries little weight in the index when using the large estimated elasticity of substitution. But with an elasticity of 10 or smaller, the price index decline is much greater, over 2.7 percentage points during this policy window. Other policy changes also tend to be associated with slightly faster declines in the prices indices.

The estimating equation for the difference-in-differences specification uses the fact that minimum efficiency regulations and Energy Star changes occurred for different appliances at different times, such that appliances not experiencing a change serve as controls for those that do. For these estimates we pool price indices for all appliances and run the following estimating equation:

$$\Delta \ln P_{j,t} = \beta_0 + \beta_1 ME_{j,t} + \beta_2 ES_{j,t} + \alpha_j + \gamma_t t + \mu_{i,m} + \varepsilon_{it}, \quad (12)$$

where $\Delta \ln P_{j,t}$ is the log difference of the price index for product j , where j spans the four appliances considered (washing machines, dryers, refrigerators, air conditioners), α_j and γ_t are fixed effects for each appliance and each time period time period, respectively, and the policy variables $ME_{j,t}$ and $ES_{j,t}$ are plus/minus six-month indicator variables, specified for applicable policy changes for each appliance j . For some specifications we consider appliance-by-month-of-year fixed effects ($\mu_{i,m}$)

to account for seasonality, which is more noticeable in some appliances than others (like room air conditioners).

The difference-in-differences estimates, like the difference estimates, are less than an ideal natural experiment, both due to the anticipated nature of the policy changes and because there may be joint dependency in new appliance introductions. For example, if a new energy efficiency standard causes introduction of a new washing machine model, then it may be economic for the manufacturer to introduce other appliances at the same time. To the extent that there is joint dependency in manufacture or sale of different appliances, using these complementary goods as controls should generally underestimate the size of the welfare impacts. Because different appliances may be better or worse controls than others, we consider specifications with different sets of appliances.

While some of the large introductions of new appliances appear to be associated with timing of minimum efficiency (ME) or Energy Star (ES) threshold, there are a few cases where timing is off by a considerable margin, our identification strategy misses, and thus likely underestimates induced welfare gains. The clearest example is a large introduction of new refrigerators in January 2007 (see figure 2 and 3). While this large introduction of refrigerators is beneficial for consumers, only standards for washing machine changed at this time; the Energy Star changes for refrigerators happened later. Thus, if this large introduction was caused, in part, by anticipated future changes in the Energy Star threshold, our identification strategies (both differences and difference-in-differences) do not capture it; we implicitly assigning these "treatment" observations to the "control," thereby underestimating the consumer benefits of increasing the ES threshold.

Difference-in-differences estimates are reported in Table 5. The first two columns consider specifications with only washing machines and refrigerators, with the first column excluding seasonal controls and the second column including them. The next two columns add room air conditioners to the specification as a control, again without and with seasonal controls. The last two columns add dryers to the specification. Different sets of results are reported for the three welfare-based price indices, P^* , $P^{\hat{\sigma}}$, and P^{10} . All specifications indicate more rapid price declines during the policy periods, and most indicate an accelerated decline (i.e., welfare improvement) of between roughly 0.3 to 0.6 percentage points per period. Many of the specifications show statistical significance for the ES policies, but most ME policy windows are not statistically significant, even though the estimated impacts are similar in magnitude. Nevertheless, the results strongly suggest no harm, and probably consumer welfare improvement due to price declines and product introductions induced by changes in standards, all excluding benefits from reduced pollution externalities.

7 Competition and Innovation

In this section we take a closer look at the mechanisms that underlie price index declines and how changes in standards could affect them. The mechanism appears to be related to new product introductions, which are often induced by changes in standards. We pay particular attention to the way new product introductions cause reductions in prices of own-manufacturer products versus reductions in prices by competing manufactures. Similar to the findings from [Broda and Weinstein \(2006\)](#) and others, we find that new product introductions cause a greater influence on own-manufacturer prices than competing-manufacturer prices.

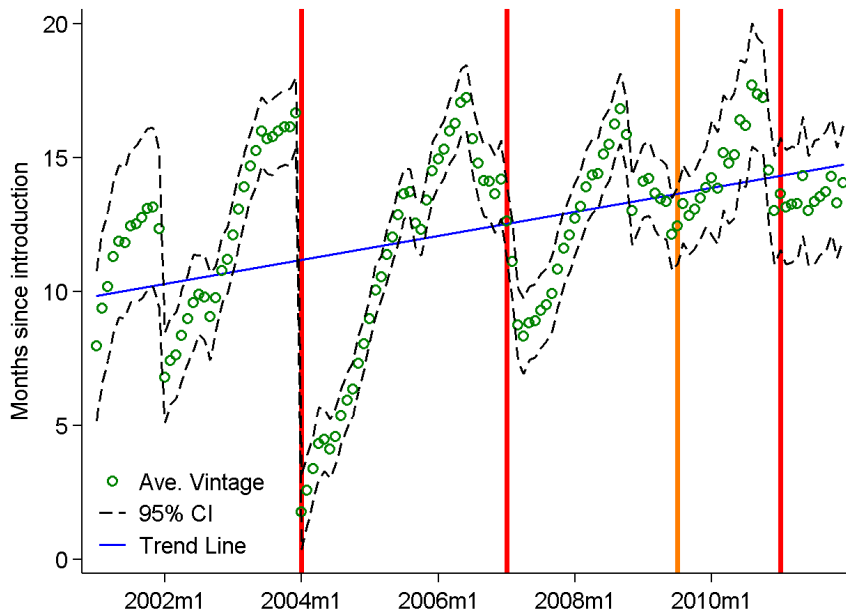
7.A Product Entry and Average Vintage

We present evidence above that consumers substitute toward new models during times when energy efficiency standards change, especially around the 2004 minimum efficiency change for washing machines. This standard caused a marked shift from top-loading to front-loading washing machines, which use less water and are more energy efficient. Another way to show substitution toward newer models is to plot the sales-weighted average vintage of appliances sold, where vintage is measured as the number of months since a model was first introduced in the market. We plot average vintage of clothes washers sold in figure 4. The figure shows sharp declines in average vintage, especially around the 2004 change in minimum efficiency. For later policy changes, we find similar, though smaller, declines that sometimes precede the policy change. In the online appendix we show graphs of average vintage for all appliances.

One explanation for the pattern of price declines observed earlier is that policy-driven entry of new models enhances competition, forcing manufactures to lower prices of older vintages. For any given model of an appliance, regardless of vintage, the lower average vintage, the more new and presumably higher-quality models are in the market with which it must compete. By forcing exit and entry, standards may significantly alter the distribution of vintages and thereby affect innovation, competition and price.

A possible concern with interpreting the data in figure 4 is that a decline in average vintage may not be solely due to the standard changes. For example, average vintage also declines during early months of 2002, 2006 and 2008, when no policy changes occurred. These drops in average vintage may result from a large firm's strategy to introduce models in order to glean revenue share from competitors. In order to provide evidence that the large drop in average vintage was due to the 2004 policy change, we calculated the sales-weighted average energy consumption (kWh) and operating costs of clothes washer during the period. Energy consumption of individual models are obtained from the Federal Trade Commission and matched with the NPD data. The present value

Figure 4: AVERAGE VINTAGE OF CLOTHES WASHERS, 2001-2011



Vintage indicates the number of months since a product was introduced. Each point represents 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.

operating cost of model $-j$ at time t , denoted as $PVOC_{jt}$, is calculated using the equation:

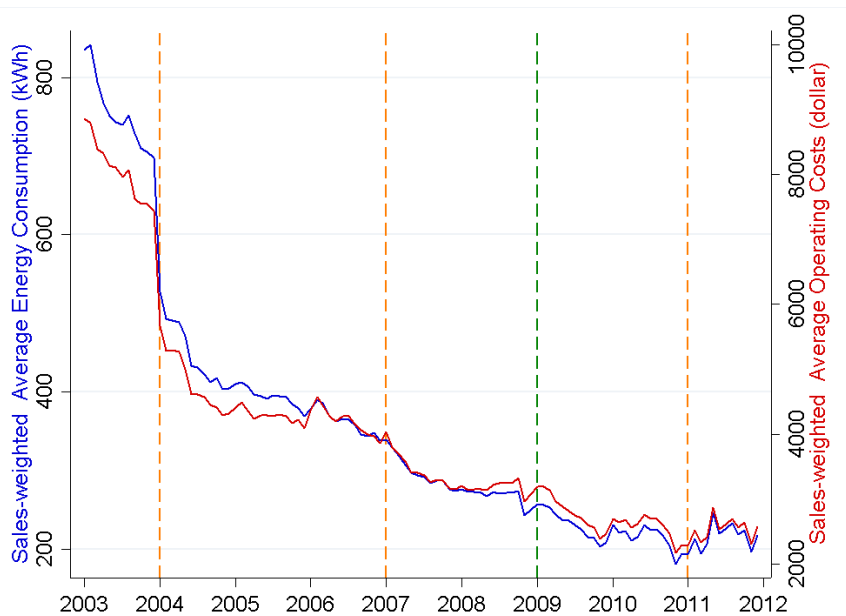
$$PVOC_{jt} = \sum_{y=0}^Y EC_j \cdot PE_t \cdot (1 + r_t)^{-(y+0.5)} \quad (13)$$

where EC denotes annual electricity consumption (in kWh) of product j , PE is the seasonally adjusted national average electricity price, r is the discount rate proxied by the 10-year U.S. Treasury bill rate, and y is the number of years the appliance is used up to its lifetime Y .

Figure 5 summarizes the calculated sales-weighted average energy consumption and operating costs for clothes washers sold during the study period. The orange vertical lines represent the simultaneous ME and ES policy changes and the green vertical line represents the ES policy change. We observe an especially large improvement in both energy efficiency measures around the policy change in 2004. This coincides with the large drop in average vintage in figure 4, which provides a clear indication that energy efficiency standard changes had a role in product entry and exit, at

least in 2004.

Figure 5: AVERAGE ENERGY CONSUMPTION AND OPERATING COSTS OF CLOTHES WASHERS, 2001-2011



Average energy consumption is calculated by combining the NPD data with the Federal Trade Commission (FTC). Annual energy consumption is measured using the DOE's methodology. The operating costs represent the discounted lifetime operating cost of a particular model
Source of Basic data: The NPD Group; FTC.

7.B Average Vintage and Competition

To examine the link between average vintage (a measure of competitive pressure) on price declines, we estimate the following reduced-form regression model:

$$\begin{aligned}
 p_{it} = & \alpha_i + \beta_0 \overline{vintage}_{-i,t} + f(vintage_{it}) \\
 & + g(vintage_{it}) \overline{vintage}_{-i,t} + month_k + \varepsilon_{it}
 \end{aligned}
 \tag{14}$$

where p_{it} denotes the price of model i at time t , $\overline{vintage}_{-i,t}$ is the average vintage (weighted by current sales) of all models excluding i at time t , and $f(vintage)$ and $g(vintage)$ are restricted cubic splines of model-specific vintage, representing number of months 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.

We cannot use time period fixed effects because $\overline{vintage}_{-i,t}$ is highly correlated across observations within a time period, given each excluded model is a tiny share of the 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.

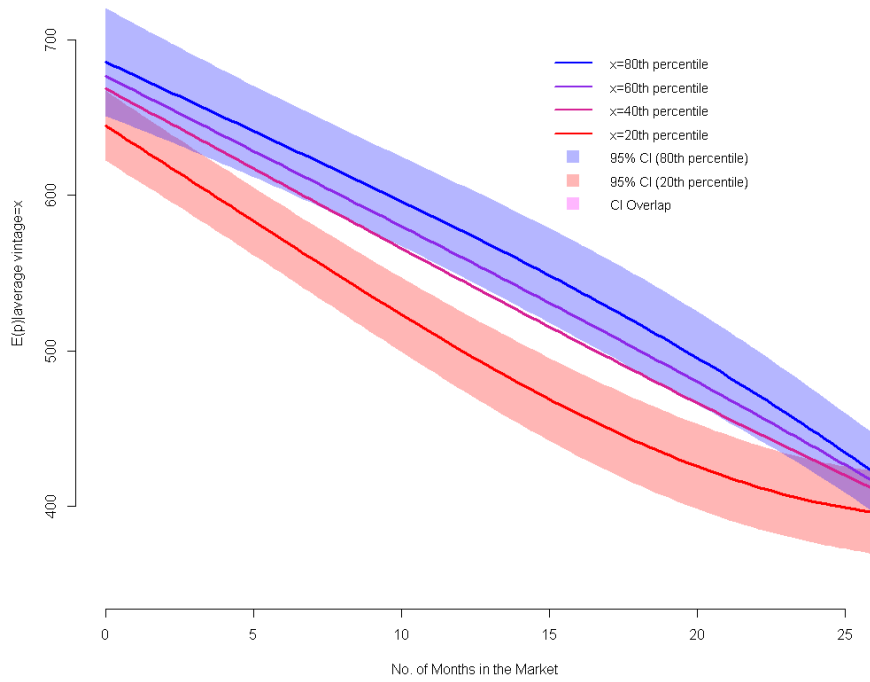
We use the estimates from equation 14 to predict the price trend of a typical clothes washer holding average vintage constant at different quantiles. Figure 6 plots this predicted price across the first two years of a clothes washer in the market, holding average vintage equivalent to about 10 months (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 6 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 percent price increase (see Table 7). Significance tests are summarized in Table 6.

We now 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 disentangle the influence of average vintage into cannibalization and external competition. To accomplish this, we decompose average vintage into own-firm average vintage and other-firm average vintage. 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 above, we consider interactions between own-model vintage and average vintage measures.

$$\begin{aligned}
 p_{i,c,t} = & \alpha_i + \beta_1 \overline{vintage}_{-i,c,t} + \beta_2 \overline{vintage}_{-c,t} + f_c(vintage_{i,t}) + \\
 & + f_c(vintage_{i,t}) \overline{vintage}_{-i,c,t} + f_c(vintage_{i,t}) \overline{vintage}_{-c,t} + month_k + \varepsilon_{it} \quad (15)
 \end{aligned}$$

Using the estimates from equation 15 we predict the price trend of a typical clothes washer holding average vintage of models within brands constant. Panel (a) in Figure 7 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

Figure 6: 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 14 during its first two years. We estimate equation 14 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.

(60th percentile) and 17 months (80th percentile). We make this prediction assuming other-brand average vintage is equivalent to about 10 months (20th percentile).¹¹ We find no statistically significant difference between trend lines in different months. Panel (b) plots the predicted price trend of a typical clothes washer holding average vintage between brands constant at 20th, 40th, 60th and 80th percentile. The difference between the trend line at 10 months and at 15 months is statistically significant (Figure 7). Reducing the average vintage from 15 months to 10 months is associated with a 3 percent price decrease, all else the same (see Table 7).

Because the clothes washer market is dominated by large integrated manufacturers with several subsidiary brands, we examine 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 7 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).¹² All else the same, reducing within-manufacturer average vintage from 16 months to 9 months is associated with a 5 percent faster price decline, a statistically significant difference. 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).

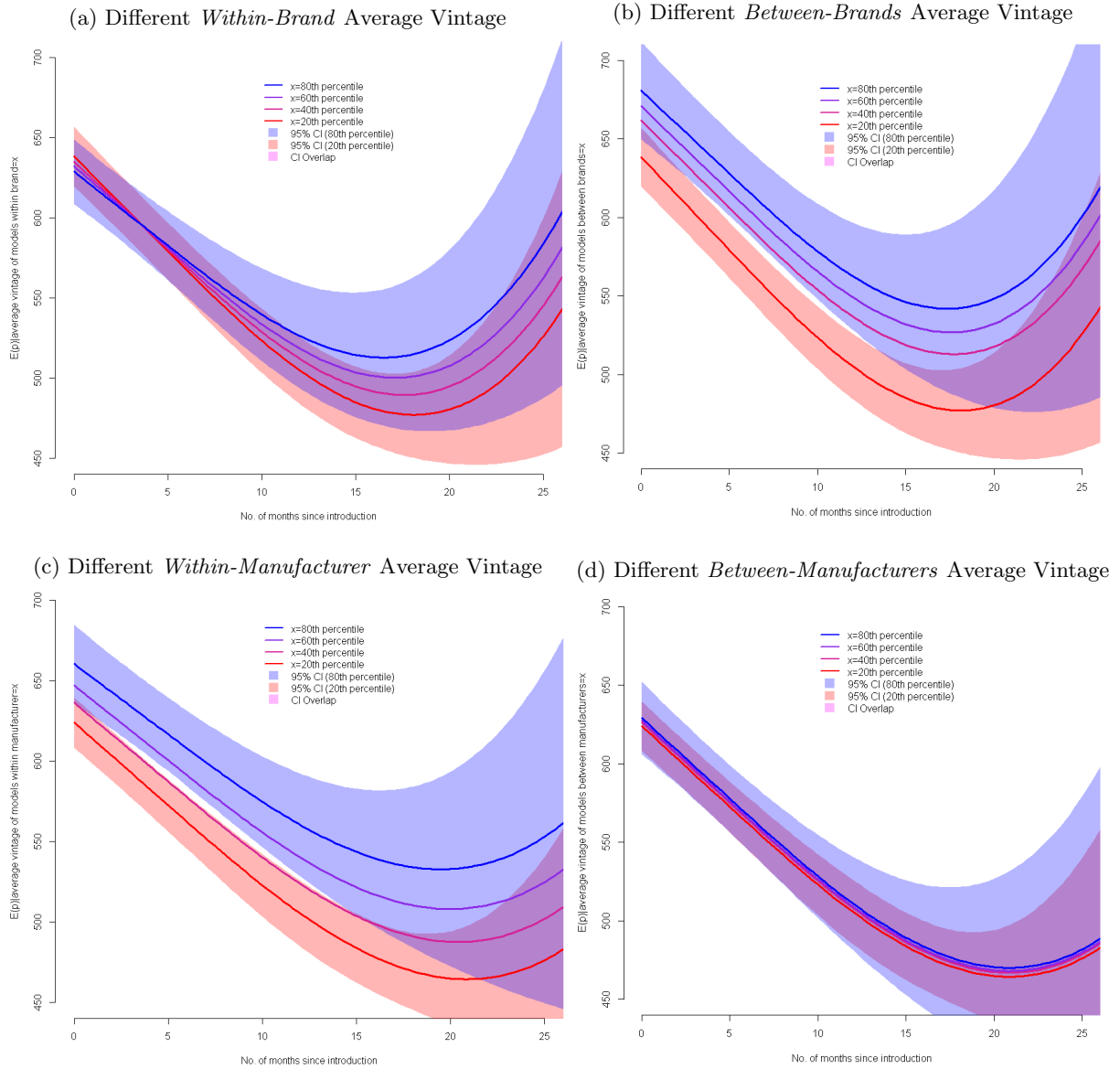
To see if cannibalism is unique to appliances that had more stringent energy efficiency standards over the sample period, we also consider refrigerators, room air conditioners and clothes dryers. No minimum efficiency standards were implemented for these appliances during the sample period, although refrigerators experienced changes in Energy Star certification in 2004 and 2008. We use the estimation strategy presented in equation 15 for these appliances. Table 7 presents the regression results using equation 14 for clothes dryers and table 8 reports refrigerators and room air conditioners.

Interestingly, we find the same pattern in for clothes dryer prices as we do for washing machines, with cannibalism at both the brand and manufacturer levels (Table 7). We do not observe cannibalism at the manufacturer level for room air conditioners or refrigerators (Table 8), although cannibalism tends to drive down unit price at the brand level for refrigerators. It seems plausible that pricing for dryers is influenced by washing machines, since consumers often purchase washers and dryers simultaneously. Findings for refrigerator prices may be due to stronger seasonality, as price discounts tend to occur during the first and last quarter of the year when the refrigerator market generally has more price declines and more new models. The evidence suggests

¹¹In online appendix (Appendix H) we show plots that hold other-brand average vintage at 13 months (40th percentile), 14 months (60th percentile) and 15 months (80 percentile).

¹²We repeat this prediction for different other-manufacturer average vintage percentiles in the online appendix (Appendix H).

Figure 7: LIFE CYCLE PRICING OF CLOTHES WASHERS



Each solid line shows a predicted price trend using equation 15 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 15 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.

an association between standards and increased cannibalism, a pattern that has been observed more generally (Broda and Weinstein, 2006).

8 Discussion and Conclusion

Contrary to some views that more stringent energy efficiency standards are costly to consumers, primarily due to higher upfront costs associated with more energy efficient appliances, we find no evidence indicating that stricter energy efficiency policies increase prices or reduce consumer welfare in markets of regulated appliances. At best, we see evidence of faster price declines while consumers substitute to new appliances as they are introduced, both indicating welfare improvement. Overall, consumers gain, although depending on assumptions about substitutability between new and continuing appliances, some gains may not be statistically significant.

What might explain this counterintuitive effect of standards on consumer welfare? One theory is that standards make heterogeneous products more homogeneous, and thereby increase competition as proposed by Ronnen (1991). Another possibility is that standards facilitate innovation (Jaffe and Palmer, 1997). We find little evidence of competition as a mechanism, since entry of other-manufacturer products has little influence on own-manufacturer prices. In contrast, we find evidence supporting policy-induced innovation, wherein firms lower prices of older models as they are forced to introduce new models meeting new, stricter efficiency standards. Firms may reduce prices as a form of intertemporal price discrimination in order to extract rents from consumers with different demands for the latest technology (Stokey, 1979). Firms may also lower prices as costs decline over time, potentially due to economies of scale or learning-by-doing. If, however, firms' pricing were solely due to declining production costs then introduction of new products should not influence the price, all else the same.

Presumably imperfectly competitive firms would strategically time product entry, staggering introduction of new products so as to maximize potential novelty. Although we do not 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. Figures 4 and 5 show how the distribution of product vintages shifts periodically, with average vintage and energy efficiency measures dropping sharply right around the time of standard changes. This pattern in product vintages implies that standards may force more rapid entry and exit of models, thereby altering the distribution of vintages and affecting innovation and competition. 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 product introductions on price more significant than in other periods. Of course, events besides standard changes could bring about synchronized timing of product entry.

We also find evidence to suggest that most and perhaps all the price declines associated with average vintage stem from 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 in our sample. One interpretation of these observations 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 introduce new products that satisfy 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 modelling assumptions may not fully capture. The CES utility model that underlies our index calculations can embody heterogeneous underlying preferences of individual discrete choice models, but the assumptions may be restrictive. It is plausible and perhaps likely that some customers lose as old models preferred by some are forced to exit as a result of standards, even while most customers gain. Future work may develop a better account of heterogeneous preferences and the distribution of benefits across different kinds of customers. For example, [Houde and Spurluck \(2015\)](#), using the same data that we have, employed revealed preference approach that allowed them to calculate a price-adjusted quality index and welfare implications of standards. Their methods appear to generate similar results to ours.

A second caveat is that 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 positive correlation of entry and exit of models among major appliances, which might be a result of large manufacturers' attempt to reduce overhead and logistical costs associated with introducing new appliances at different time periods. This caveat, however, likely makes our estimates more conservative; benefits to consumers could be greater than our estimates imply.

A third caveat is that we do not observe individuals who purchased used appliances, or otherwise accounted for a no-purchase option. While this is a limitation of the analysis, it is one that also understates the benefits of regulation. These benefits would be reflected in the overall demand for new appliances, not just substitution between them. This demand would presumably

be downward sloping, such that purchases of new appliances and total consumer surplus would increase, *ceteris paribus*, as the price index falls. We implicitly omit this consumer surplus from the associated price decline, which would depend on the elasticity of substitution between each appliance and all other goods.

A fourth caveat is that this study does not consider firms' profits. It is quite possible that firms that manufacture appliances experience profit losses from stricter efficiency standards, as they re-optimize their menu of products and processes (Whitefoot et al., 2013). If, however, the appliance industry is sufficiently competitive, even if monopolistically so, equilibrium economic profits are presumably small relative to consumer benefits, regardless of standards.

Stepping back from the details of our analysis, it is useful to contemplate what the data might have shown if minimum efficiency standards were truly costly. Because the minimum standard affected the manufacture of washers but not their sale, there is no a priori reason to expect a sharp discontinuity in average vintage at the time of the policy change, a change that we nevertheless do observe. If the banned washers were both generally preferred and lower cost than the new washers, we might have seen a large build-up and carryover of old inventory into the newly regulated environment, and slow subsequent adoption of the new washers. Moreover, banned washers would have become a scarce, non-renewable commodity that should have seen increasing prices. Instead, we see the opposite: a fall in prices of continuing models and, despite that price decline, a dramatic shift in purchases from old models to new models. These facts are very hard to reconcile with anything but generally improving consumer welfare, irrespective of reduced pollution externalities associated with lower energy use.

More generally, these findings clarify that the evaluation of energy efficiency standards requires consideration of more than pollution externalities and the existence, size, and causes of the energy efficiency gap. Markets for energy-consuming durable goods markets contain additional market failures, like imperfect competition and public-good aspects of innovation, as well as consumer behavioral anomalies. 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.

Finally, and somewhat askew from the main thrust of the paper, we present evidence, akin to Broda and Weinstein (2006), Broda and Weinstein (2010), and Redding and Weinstein (2018), that conventional cost of living indices, like the CPI, may not adequately account for quality changes and introductions of new products. Our price indices, built on model-specific data and accounts of product entry and exit, show more rapid declines than related components in the CPI (Figure G.5). The difference results mainly from building indices from same-product price changes and partly from our account of substitution to new products.

Table 4: AVERAGE CHANGE IN PRICE INDICES AND THE RATIO OF SHARES OF CONTINUING MODELS IN TWO CONSECUTIVE PERIODS, WASHERS VS. REFRIGERATORS VS. ROOM AC VS DRYERS, 2002-2011.

Period	P^{ME}	P^F	P^*	$P^{\hat{\sigma}}$	P^{10}	$\frac{\lambda_t}{\lambda_{t-1}}$
Clothes Washers						
Pre-2004	-0.648	-0.651	-0.467	-0.477	-0.578	0.991
2004 ME & ES Policy	-1.107	-1.107	-0.834	-1.026	-2.766	0.916
Post-2004 Policy	-0.359	-0.359	-0.136	-0.140	-0.181	0.996
Pre-2007 Policy	-1.271	-1.270	-0.911	-0.920	-1.010	0.991
2007 ME & ES Policy	-1.501	-1.492	-1.250	-1.271	-1.474	0.980
2008 ES Policy	-1.206	-1.812	-0.742	-0.747	-0.799	0.995
2009 ES Policy	-2.299	-2.239	-2.128	-2.133	-2.183	0.994
2011 ME & ES Policy	-2.065	-2.000	-1.596	-1.613	-1.783	0.983
Refrigerators						
Pre-2004	-1.216	-1.218	-1.031	-1.055	-1.146	0.990
2004 ME & ES Policy	-1.242	-1.242	-0.967	-1.015	-1.195	0.980
Post-2004 Policy	-0.778	-0.782	-0.560	-0.587	-0.688	0.989
Pre-2007 Policy	-0.962	-0.960	-0.605	-0.619	-0.670	0.994
2007 ME & ES Policy	-1.475	-1.462	-1.210	-1.410	-1.226	0.942
2008 ES Policy	-1.317	-1.311	-1.183	-1.214	-1.333	0.984
2009 ES Policy	-1.168	-1.156	-0.900	-0.928	-1.031	0.988
2011 ME & ES Policy	-1.510	-1.483	-1.072	-1.071	-1.069	1.000
Room Airconditioners						
Pre-2004	-2.698	-2.380	-2.186	-2.295	-2.964	0.937
2004 ME & ES Policy	-2.491	-2.327	-2.065	-2.064	-2.060	1.003
Post-2004 Policy	1.799	1.402	1.604	1.473	0.688	0.874
Pre-2007 Policy	-1.210	-1.085	-0.733	-0.742	-0.798	0.995
2007 ME & ES Policy	-1.136	-1.121	-0.941	-0.954	-1.030	0.993
2008 ES Policy	0.108	0.019	-0.011	-0.184	-1.225	0.950
2009 ES Policy	-0.346	-0.410	-0.222	-0.213	-0.161	1.005
2011 ME & ES Policy	-3.111	-3.056	-2.808	-2.809	-2.813	1.000
Clothes Dryers						
Pre-2004	-0.640	-0.642	-0.455	-0.496	-0.576	0.990
2004 ME & ES Policy	-0.706	-0.716	-0.431	-0.439	-0.453	0.998
Post-2004 Policy	-0.298	-0.298	-0.228	0.241	-0.267	0.910
Pre-2007 Policy	-0.936	-0.934	-0.579	-0.613	-0.680	0.991
2007 ME & ES Policy	-1.059	-1.052	0.808	-0.880	-1.023	0.981
2008 ES Policy	-0.975	-0.936	-0.719	-0.760	-0.842	0.989
2009 ES Policy	-1.514	-1.471	-1.257	-1.271	-1.299	0.966
2011 ME & ES Policy	-1.635	-1.587	-1.218	-1.241	-1.285	0.944

The table reports the percent change in each price index during the referenced policy change. Periods in boldface font indicate a policy change for the given appliance. Each policy 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. Only refrigerators experienced Energy Star (ES) policy changes within the sample period. P^{ME} is the Marshall-Edgeworth price index; P^F is the Fisher price index; P^* is the CES-based index for common goods; $P^{\hat{\sigma}}$ is the CES-based index with new and exiting models and the estimated elasticity of substitution (101 for clothes washers; 44 for refrigerators, 66 for room air conditioners, and 28 for clothes dryers); P^{10} is the CES-based index with a substitution elasticity of 10. The ratio $(\lambda_t/\lambda_{t-1})$ gives the average share of expenditures on common goods (continuing models) in the current period relative to the previous period, where a value less than one implies substitution toward new goods and a welfare improvement, all else the same.

Table 5: RESULTS FROM ESTIMATING THE AVERAGE EFFECT OF THE POLICY CHANGE (DIFFERENCE-IN-DIFFERENCES APPROACH)

Models/Variables	(1)	(2)	(3)	(4)	(5)	(6)
	ΔP^*					
ME and ES	-0.005 (0.004)	-0.005 (0.004)	-0.003 (0.004)	-0.003 (0.004)	-0.003 (0.003)	-0.003 (0.003)
ES Only	-0.006* (0.003)	-0.006** (0.003)	-0.005* (0.003)	-0.005** (0.002)	-0.005*** (0.002)	-0.005*** (0.002)
Constant	-0.076*** (0.001)	-0.073*** (0.003)	-0.004*** (0.002)	-0.008*** (0.001)	-0.066** (0.026)	-0.064*** (0.024)
Adj. R-squared	0.549	0.640	0.320	0.418	0.518	0.510
Observations	219	219	325	325	436	436
	$\frac{\lambda_t}{\lambda_{t-1}}$					
ME and ES	-0.012 (0.026)	-0.012 (0.027)	-0.017 (0.023)	-0.017 (0.024)	-0.027 (0.024)	-0.027 (0.024)
ES Only	0.019 (0.020)	0.019 (0.020)	0.015 (0.016)	0.015 (0.016)	0.004 (0.013)	0.004 (0.013)
Constant	0.999*** (0.001)	0.997*** (0.006)	0.990*** (0.009)	0.994*** (0.010)	0.987*** (0.006)	0.987*** (0.008)
Adj. R-squared	0.270	0.192	0.277	0.357	0.146	0.115
Observations	221	221	328	325	436	436
	$\Delta P^{\hat{\sigma}}$					
ME and ES	-0.005 (0.005)	-0.005 (0.004)	-0.003 (0.004)	-0.003 (0.004)	-0.004 (0.003)	-0.004 (0.003)
ES Only	-0.006* (0.003)	-0.005* (0.003)	-0.004 (0.003)	-0.004* (0.002)	-0.006*** (0.002)	-0.005*** (0.002)
Constant	-0.076*** (0.001)	-0.073*** (0.003)	-0.004*** (0.002)	-0.008*** (0.001)	-0.066** (0.026)	-0.064*** (0.024)
Adj. R-squared	0.527	0.612	0.325	0.417	0.441	0.432
Observations	219	219	325	325	436	436
	ΔP^{10}					
ME and ES	-0.008 (0.009)	-0.008 (0.009)	-0.007 (0.007)	-0.007 (0.008)	-0.010 (0.008)	-0.010 (0.008)
ES Only	-0.000 (0.007)	-0.000 (0.006)	-0.000 (0.005)	-0.000 (0.005)	-0.004 (0.004)	-0.004 (0.004)
Constant	-0.077*** (0.001)	-0.075*** (0.004)	-0.004** (0.002)	-0.008*** (0.002)	-0.067*** (0.026)	-0.065*** (0.024)
Adj. R-squared	0.259	0.236	0.261	0.285	0.190	0.165
Observations	219	219	325	325	436	436
Appliance FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Month x Ref	No	Yes	Yes	Yes	Yes	Yes
Month x AC	No	No	No	Yes	Yes	Yes
Month X Dryer	No	No	No	No	No	Yes

The table reports difference-in-difference estimates of the effects of minimum energy efficiency (ME) and Energy Star (ES) policy changes on each welfare-based price index: P^* is the CES-based index for common goods; $P^{\hat{\sigma}}$ is the CES-based index with new and exiting models and the estimated elasticity of substitution (101 for washers, 44 for refrigerators, and 66 for room air conditioners); and P^{10} is the CES-based index with a substitution elasticity of 10. The ratio $(\lambda_t/\lambda_{t-1})$ gives the average share of expenditures on common goods (continuing models) in the current period relative to the previous period, where a value less than one implies substitution toward new goods and a welfare improvement, all else the same. Columns labelled (1)-(2) include clothes washers and refrigerators; columns (3)-(4) also include room air conditioners in the sample; and columns (5)-(6) also include clothes dryers in the sample. Month x REF, Month x RAC, and Month x Dryer are intersections of month and appliance dummies for refrigerators, room ACs, and clothes dryers, respectively, to account for seasonality. 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 U.S. between 2002-2011 (The NPD Group); price indices and ratio of the share of continuing models between t and $t - 1$ (authors' calculation).

Table 6: 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.

Table 7: 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*** (0.379)		2.535*** (0.262)	
β_2 , average vintage between brands	3.145*** (0.630)		3.580*** (0.501)	
β_1 , average vintage within manufacturer		3.905*** (0.427)		4.657*** (0.262)
β_2 , average vintage between manufacturers		0.744 (0.462)		1.736*** (0.381)
Constant	719.932*** (6.322)	722.204*** (6.005)	617.112*** (4.950)	612.562*** (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 15 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.

Table 8: REGRESSION RESULTS: DEPENDENT VARIABLE - UNIT PRICE,
ROOM AIR CONDITIONERS AND REFRIGERATORS

	Room AC		Refrigerator	
	(1)	(2)	(3)	(4)
β_1 , average vintage within brand	0.158 (0.130)		4.264*** (0.411)	
β_2 , average vintage between brands	0.999*** (0.202)		4.429*** (0.739)	
β_1 , average vintage within manufacturer		0.002 (0.003)		0.137 (0.084)
β_2 , average vintage between manufacturers		1.109*** (0.175)		6.829*** (0.706)
Constant	403.189*** (3.986)	403.503*** (4.021)	1450.485*** (8.646)	1465.583*** (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 15 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.

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Appendix A The NPD Appliance Dataset: Retailers, Manufacturers and Brands.

Table A.1: Participating Retailers in the NPD Dataset.

	Actuals Included for:	Projected* Sales Included for:
Abt. TV & Appliance	Kmart	ABC Warehouse
Amazon.com	Kohls	BrandsMart
American TV	Linens n Things (Data thru 12/08)	Conns Appliance
Bernies	Lowe's	Cowboy Maloneys
Best Buy	Macys	Frys
BJ's Wholesale Club	Meijer	Home Depot
Bloomingdale	Nebraska Furniture Mart	Menards
Boscov's	PC Richard & Sons	Navy Exchange
Circuit Data (Data thru 2/09)	Pamida	Queen City Appliance
Dillard's	RC Willey	REX Stores
Fortunoff (Data thru 5/09)	Sears	Vanns
Fred Meyer	Shopko	
Gottschalks (Data thru 3/09)	Target	
HH Gregg	Ultimate Electronics	
JC Penney		

Note: Projected refers to the fact that NPD included estimates of sales for this subset of retailers in their data. They claim that the share of overall market sales was no greater than 5 percent for all projected retailers combined for a given time period.
Source: [Spurlock \(2013\)](#).

Table A.2: 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 U.S. (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 B 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 U.S. between 2002 and 2011. Estimated total revenue and total units sold for the entire U.S. market is from the NPD Group. Total shipment for each appliance was collected from the Association of Home Appliance Manufactures (AHAM). Tables B.3 and B.4 show market share estimates for clothes washers and dryers, respectively. Tables B.5 and B.6 show market share estimates for refrigerators and room ACs, respectively.

Table B.3: MARKET SHARE OF SAMPLED CLOTHES WASHERS, 2002-2010.

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	Ave.
U.S. Market (Total)											
Total revenues	3,186	3,068	3,270	4,146	4,251	4,425	3,980	3,786	4,231	3,638	
Total sales	7,074	6,566	7,113	8,554	8,047	7,964	7,494	7,074	7,994.68	7,010	
Total shipments	7,700	8,100	8,800	9,200	9,500	8,825	8,292	7,865	8,005	7,586	
With Masked Models											
Revenues	786	875	1,009	1,216	1,334	2,163	1,984	2,261	1,190	1,184	
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	681	671	804	907	1,621	1,577	2,010	1,188	1,183	
Sales	1,461	1,612	1,346	1,431	1,603	2,551	2,396	3,238	2,149	2,175	
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 U.S.\$ 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 U.S. Market (NPD Group); total shipment (Association of Home Appliance Manufacturers).

Table B.4: MARKET SHARE OF SAMPLED CLOTHES DRYERS, 2002-2010.

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	Ave.
U.S. Market											
Total revenues	2,202	2,188	2,480	3,046	3,050	3,306	2,951	2,852	3,008	2,763	
Total sales	6,012	5,701	6,571	7,516	6,895	6,639	6,089	5,574	6,084	5,576	
Total shipments	6,892	7,334	7,922	8,158	7,974	7,554	6,973	6,484	6,551.00	6,147	
With Masked Models											
Revenues	561	642	684	851	936	1,047	1,327	1,409	1,525	1,459	
Sales	1,742	1,918	1,884	2,155	2,227	2,265	2,468	2,452	2,813	2,700	
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	412	463	436	574	633	771	1,058	1,254	1,389	1,337	
Sales	1,215	1,329	1,073	1,287	1,372	1,508	1,768	2,090	2,461	2,437	
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 U.S.\$ 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 U.S. Market (NPD Group); total shipment (Association of Home Appliance Manufacturers).

Table B.5: MARKET SHARE OF SAMPLED REFRIGERATORS, 2002-2010.

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	Ave.
U.S. Market											
Total revenue	6,264	6,451	7,067	8,459	6,861	7,125	6,371	5,757	7,061	6,732	
Total sales	9,442	9,539	10,845	13,654	10,308	9,999	9,211	8,257	9,569	9,257	
Total shipments	9,744	10,021	10,913	11,135	11,077	10,399	9,328	8,397	9,369	8,981	
With Masked Models											
Revenues	1,468	1,606	1,775	2,127	2,236	3,464	2,723	2,824	3,340	2,984	
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	1,185	1,045	1,157	1,274	2,097	1,763	1,917	2,259	1,999	
Sales	1,732	1,831	1,617	1,589	1,679	2,242	1,8542	2,086	2,370	2,032	
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 U.S.\$ 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 U.S. Market (NPD Group); total shipment (Association of Home Appliance Manufacturers).

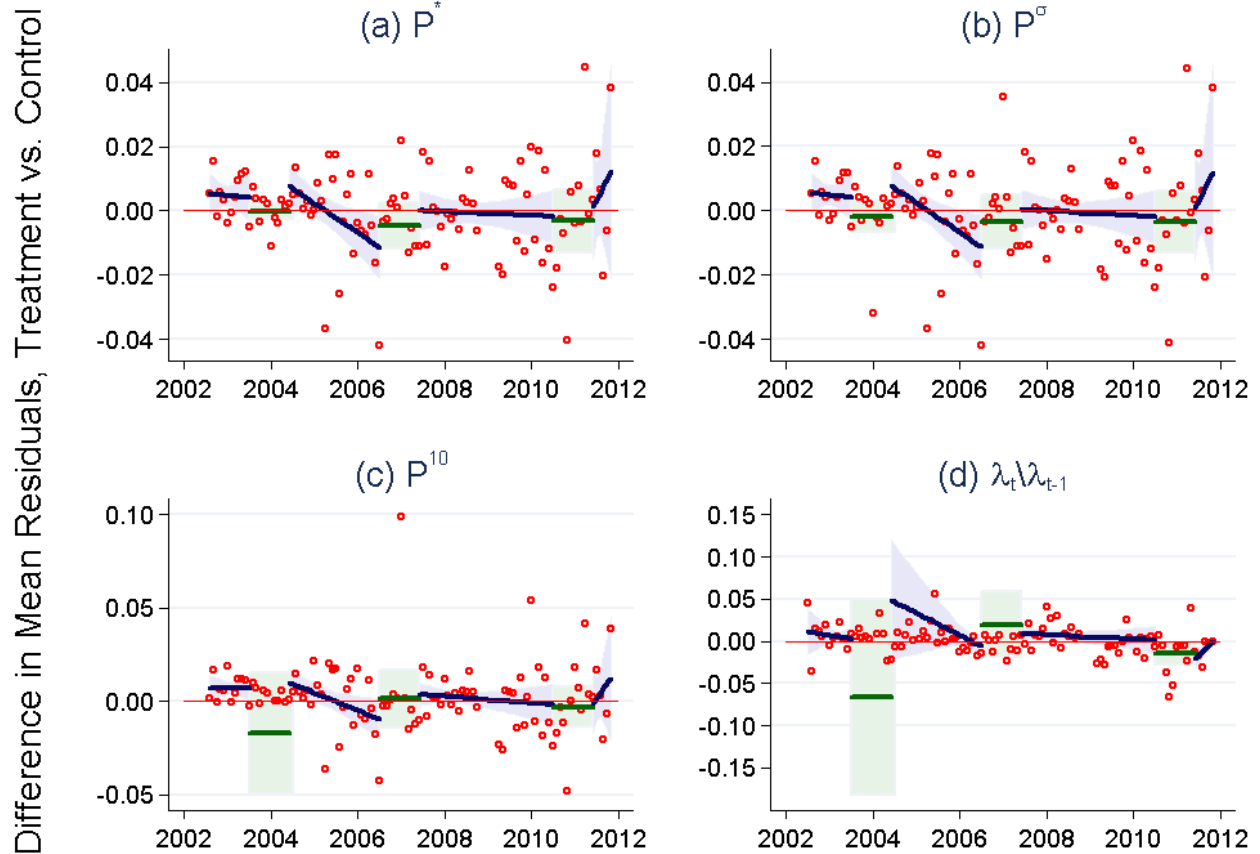
Table B.6: MARKET SHARE OF SAMPLED ROOM AIRCONDITIONERS,
2002-2010.

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	Ave
U.S. Market											
Total revenue	6,265	6,451	7,067	8,458	6,861	7,125	6,371	5,757	7,061	6,732	
Total sales	9,442	9,539	10,845	13,654	10,308	9,999	9,211	8,257	9,569	9,257	
Total shipments	9,744	10,021	10,913	11,135	11,077	10,399	9,328	8,397	9,369	8,981	
With Masked Models											
Revenues	1,468	1,606	1,775	2,127	2,236	3,464	2,723	2,824	3,340	2,984	
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	1,185	1,045	1,157	1,274	2,097	1,763	1,917	2,259	1,997	
Sales	1,732	1,831	1,617	1,589	1,679	2,242	1,854	2,086	2,370	2,031	
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 U.S.\$ 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 U.S. Market (NPD Group); total shipment (Association of Home Appliance Manufacturers).

Appendix C Examination of Residuals from the Difference-in-Differences Approach

Figure C.1: DIFFERENCE IN MEAN RESIDUALS, ME OMITTED, TREATMENT VS CONTROL

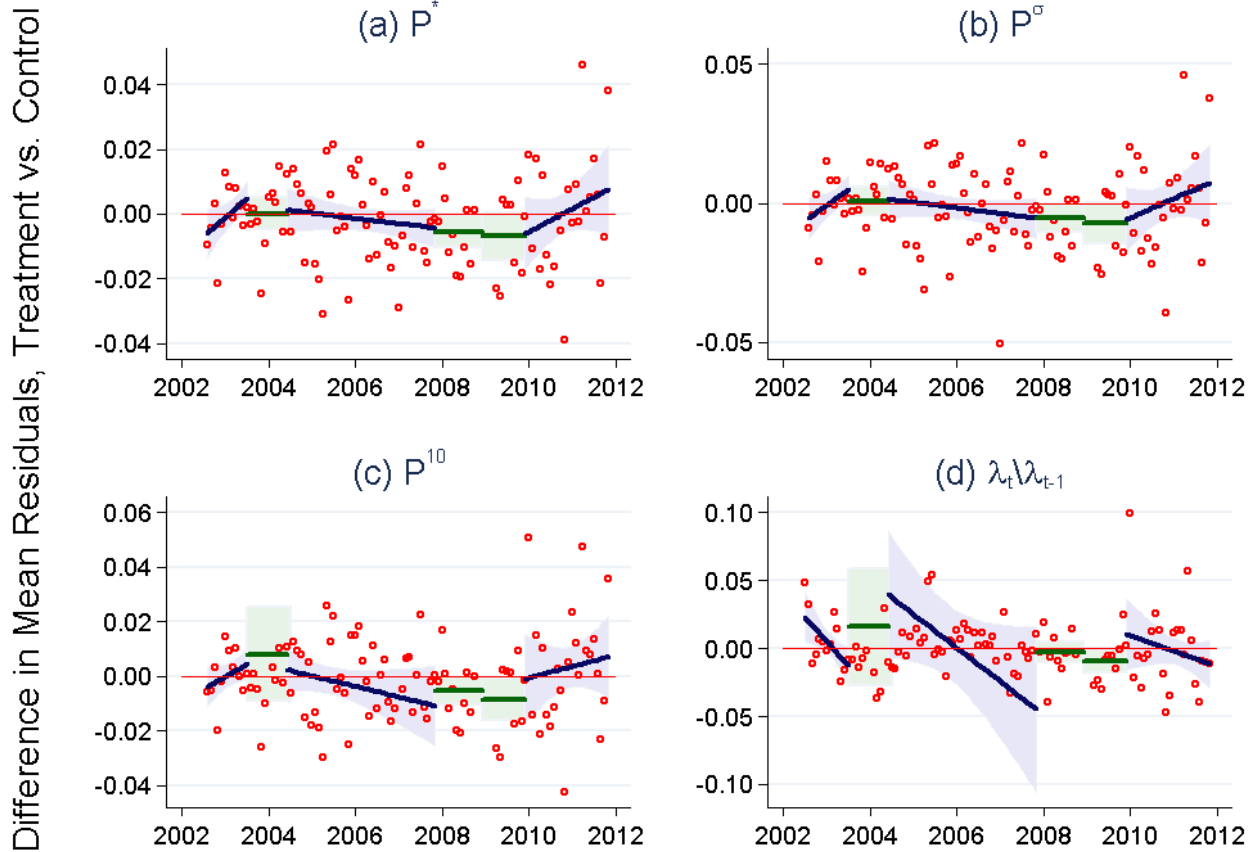


Notes: The figures above illustrate the difference in average residuals between treatment and control groups in each referenced price index. Residuals are calculated after estimating equation 12 but omitting the minimum energy efficiency standards variable, ME . Green lines and shadings correspond to mean parameter and 90% confidence interval in periods wherein an appliance is subject to a minimum energy efficiency standard. Each policy 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. P^* is the CES-based index for common goods; P^σ is the CES-based index with new and exiting models and the estimated elasticity of substitution (101 for clothes washers; 44 for refrigerators, a66 for room air conditioners, and 28 for clothes dryers); P^{10} is the CES-based index with a substitution elasticity of 10. The ratio $(\lambda_t/\lambda_{t-1})$ gives the average share of expenditures on common goods (continuing models) in the current period relative to the previous period, where a value less than one implies substitution toward new goods and a welfare improvement, all else the same. Outliers (timelines and values shown below) are omitted for better visualization.

Source of raw data: The NPD Group.

Outliers omitted in the figure.			
P^{10}		$(\lambda_t/\lambda_{t-1})$	
Year.month	Values	Year.month	Values
2004.1	-0.233	2004.1	-0.841
		2005.1	0.109
		2007.1	0.282
		2010.1	0.482

Figure C.2: DIFFERENCE IN MEAN RESIDUALS, *ES* OMITTED, TREATMENT VS CONTROL



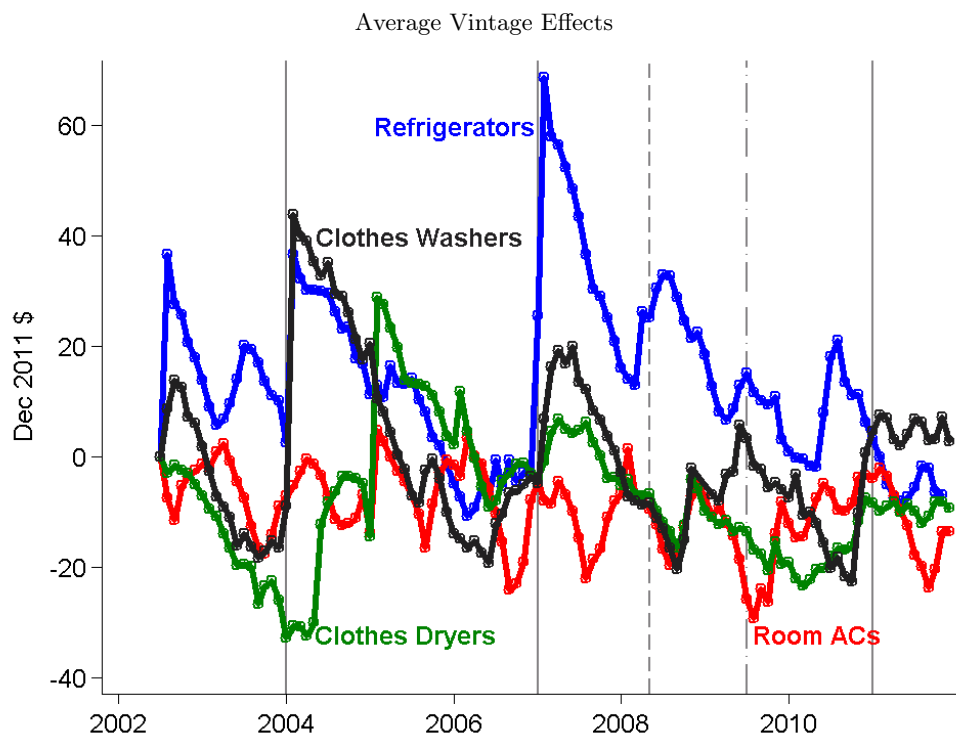
Notes: The figures above illustrate the difference in average residuals between treatment and control groups in each referenced price index. Residuals are calculated after estimating equation 12 but omitting the Energy Star variable, *ES*. Green lines and shadings correspond to mean estimated parameters and 90 percent confidence interval in periods wherein an appliance is subject to a Energy Star (*ES*) policy change. Each policy 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. P^* is the CES-based index for common goods; P^σ is the CES-based index with new and exiting models and the estimated elasticity of substitution (101 for clothes washers; 44 for refrigerators, a66 for room air conditioners, and 28 for clothes dryers); P^{10} is the CES-based index with a substitution elasticity of 10. The ratio $(\lambda_t/\lambda_{t-1})$ gives the average share of expenditures on common goods (continuing models) in the current period relative to the previous period, where a value less than one implies substitution toward new goods and a welfare improvement, all else the same. Outliers (timelines and values shown below) are omitted for better visualization.

Source of raw data: The NPD Group.

Outliers omitted in the figure.			
P^{10}		$(\lambda_t/\lambda_{t-1})$	
Year.month	Values	Year.month	Values
2004.1	-0.141	2004.1	-0.600
2007.1	0.119	2005.1	0.300
		2007.1	0.387

Appendix D Average Vintage of All Four Appliances

Figure D.3: AVERAGE VINTAGE OF CLOTHES WASHERS, REFRIGERATORS, ROOM ACs AND CLOTHES DRYERS, 2002-2011.



Notes: The figure shows sales-weighted average vintage for each appliance across time. The solid 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 U.S. dollars.

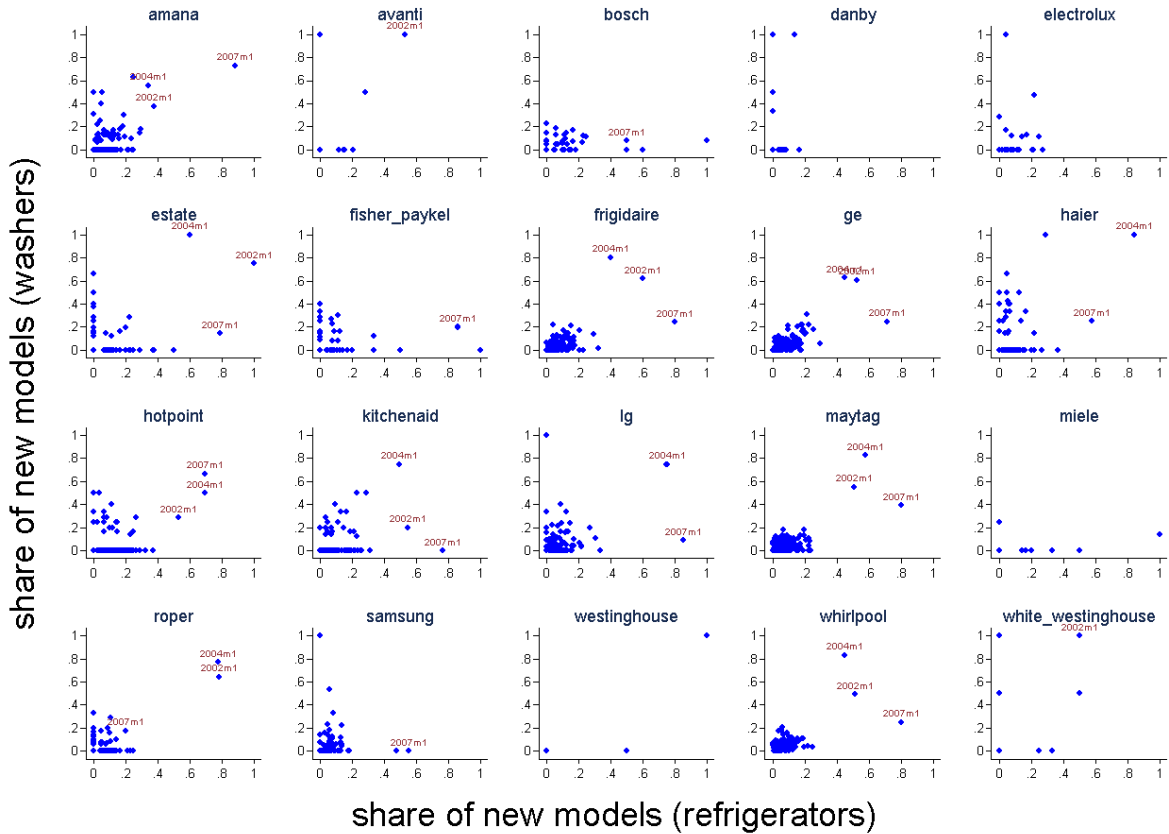
Source: Monthly sales and revenues of clothes washers sold in the U.S. between 2001-2011 (The NPD Group) and authors' calculations.

Appendix E Correlation in the Introduction of New Models Between Clothes Washers and Refrigerators at the brand level

We observe that unit price (holding quality constant), quality and consumer welfare gains for clothes washers and refrigerators follow similar trends and fluctuations, including the significant drop around 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 E.4).

Figure E.4: 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 F 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 run the regressions of price against the average vintage within and between firms, both at the brand and manufacturer levels (equation 14). The results from estimating equation 14 without masked models are presented in Table F.7. We find that the qualitative results remain the same.

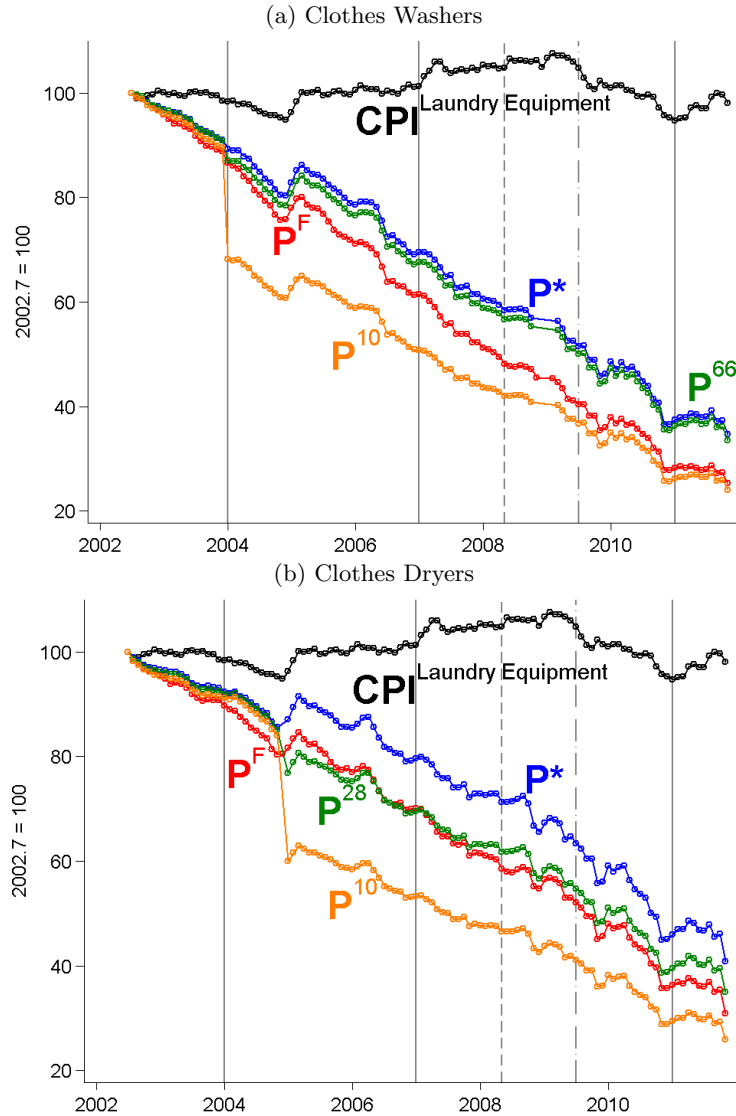
Table F.7: REGRESSION RESULTS: DEPENDENT VARIABLE – UNIT PRICE,
CLOTHES WASHERS (UNMASKED MODELS ONLY)

	(1)	(2)
β_1 , average vintage <i>within brand</i>	2.007*** (0.456)	
β_2 , average vintage <i>between brands</i>	4.011*** (0.775)	
β_1 , average vintage <i>within manufacturer</i>		3.817*** (0.468)
β_2 , average vintage <i>between manufacturers</i>		1.083* (0.561)
Constant	700.737*** (142.630)	664.264 (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 15 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.

**Appendix G Comparison between the Consumer Price Index
and the Price Indices for Laundry Equipment**

Figure G.5: ADJUSTED CPI AND PRICE INDICES FOR LAUNDRY EQUIPMENT, 2002-2011



Notes: Panels (a)-(b) show the CPI for laundry equipment and the calculated price indices for clothes washers and dryers, respectively. P^{ME} and P^F are the Marshall-Edgeworth and Fisher price indices, respectively; P^* is the CES-based index for common goods; $P^{\hat{\sigma}}$ is the CES-based index with new and exiting models and the estimated elasticity of substitution (101 for washers; 44 for refrigerators, and 66 for room air conditioners); and P^{10} is the CES-based index with a substitution elasticity of 10. The solid 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 U.S. dollars.

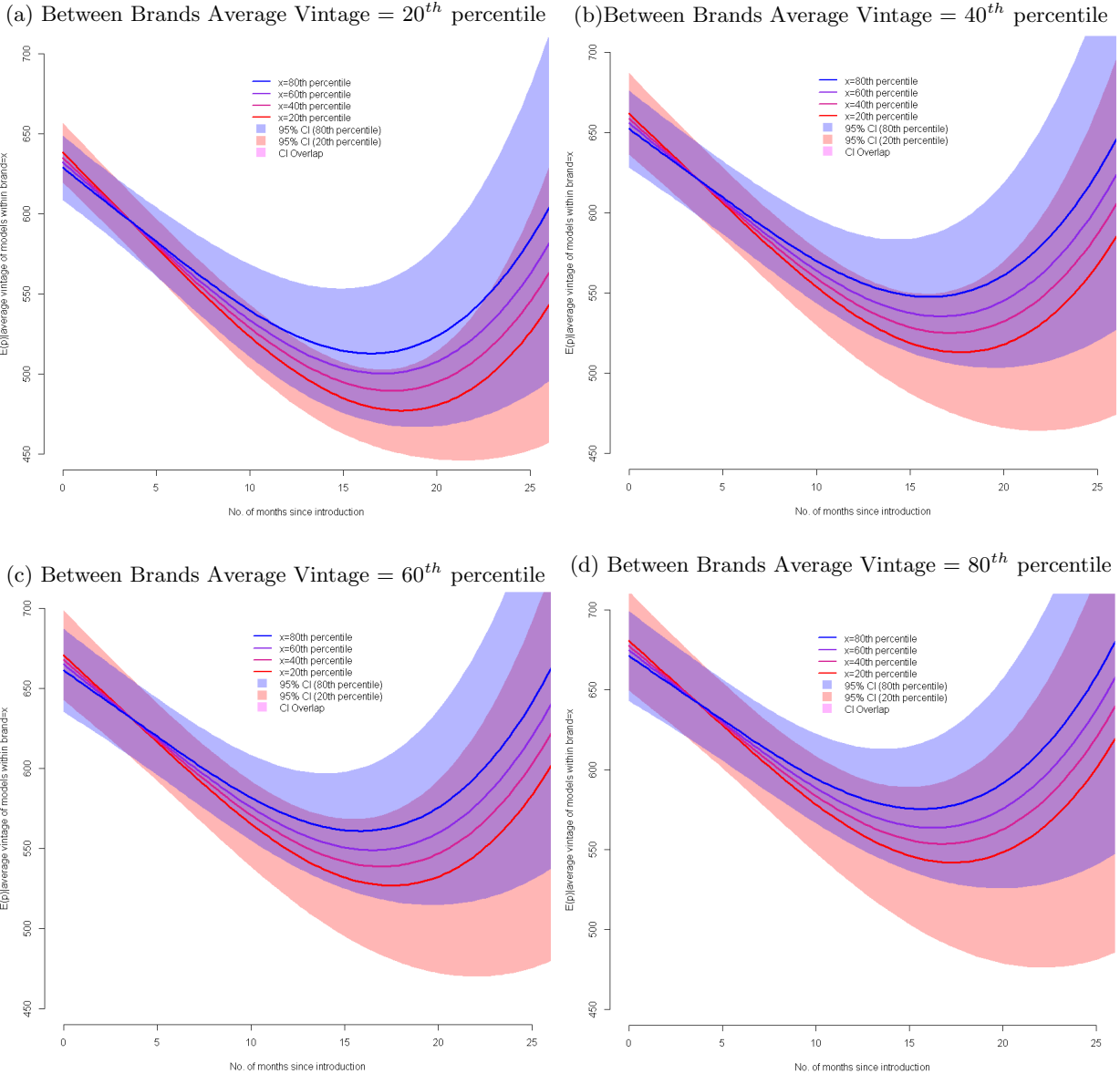
Source of raw data: Bureau of Labor Statistics; The NPD Group.

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

We use the estimates from equation 15 to predict the price trend of typical clothes washer holding average vintage of models within brands constant. Figure H.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), while Figure H.7 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 H.8 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 (80th percentile). Figure H.9 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 (80th percentile).

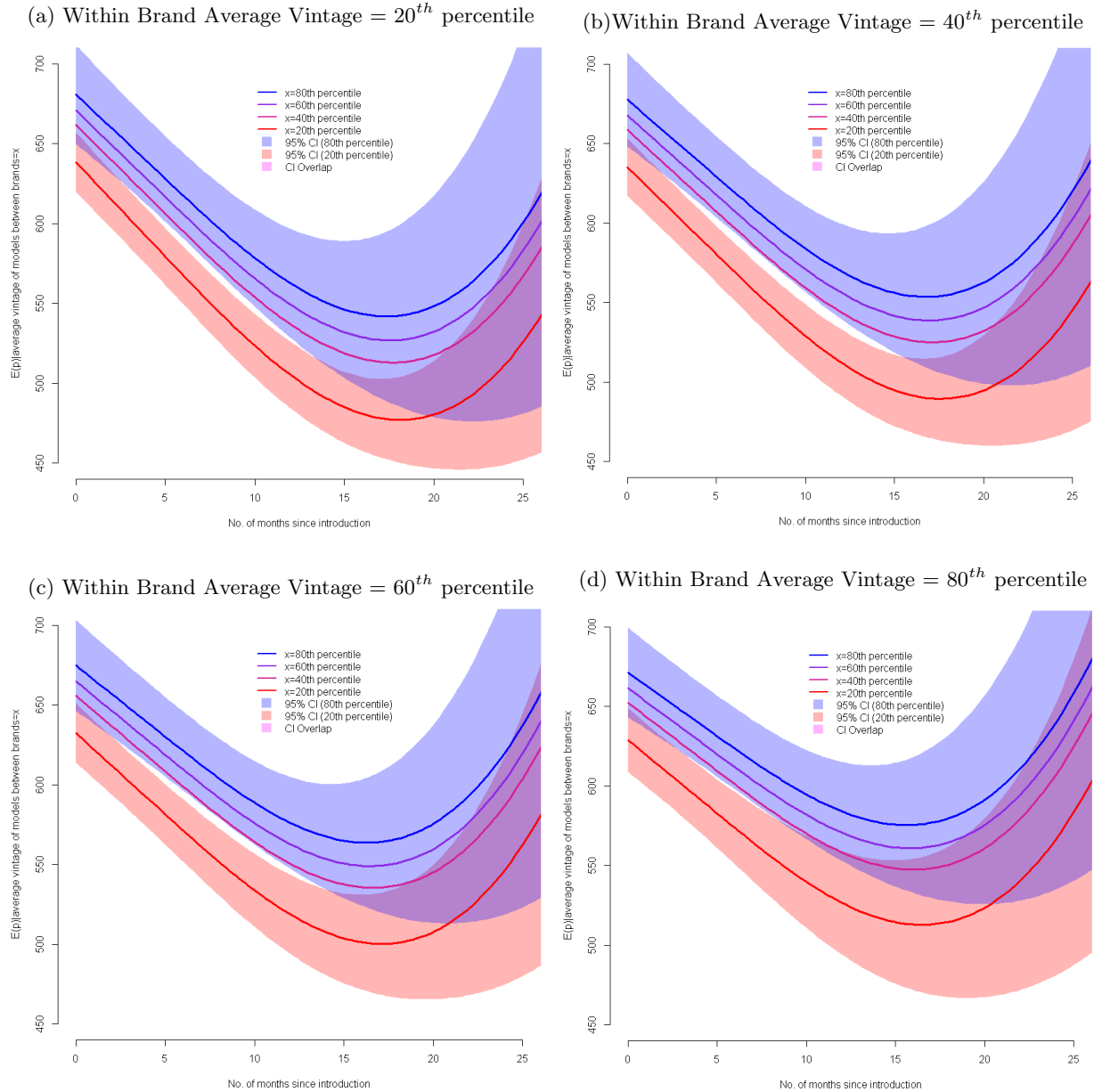
Figure H.6: LIFE CYCLE PRICING OF CLOTHES WASHERS UNDER DIFFERENT WITHIN-BRAND AVERAGE VINTAGE



The figure shows that trend in the predicted price of a representative clothes washer using equation 15 during its first two years. We estimate equation 15 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.

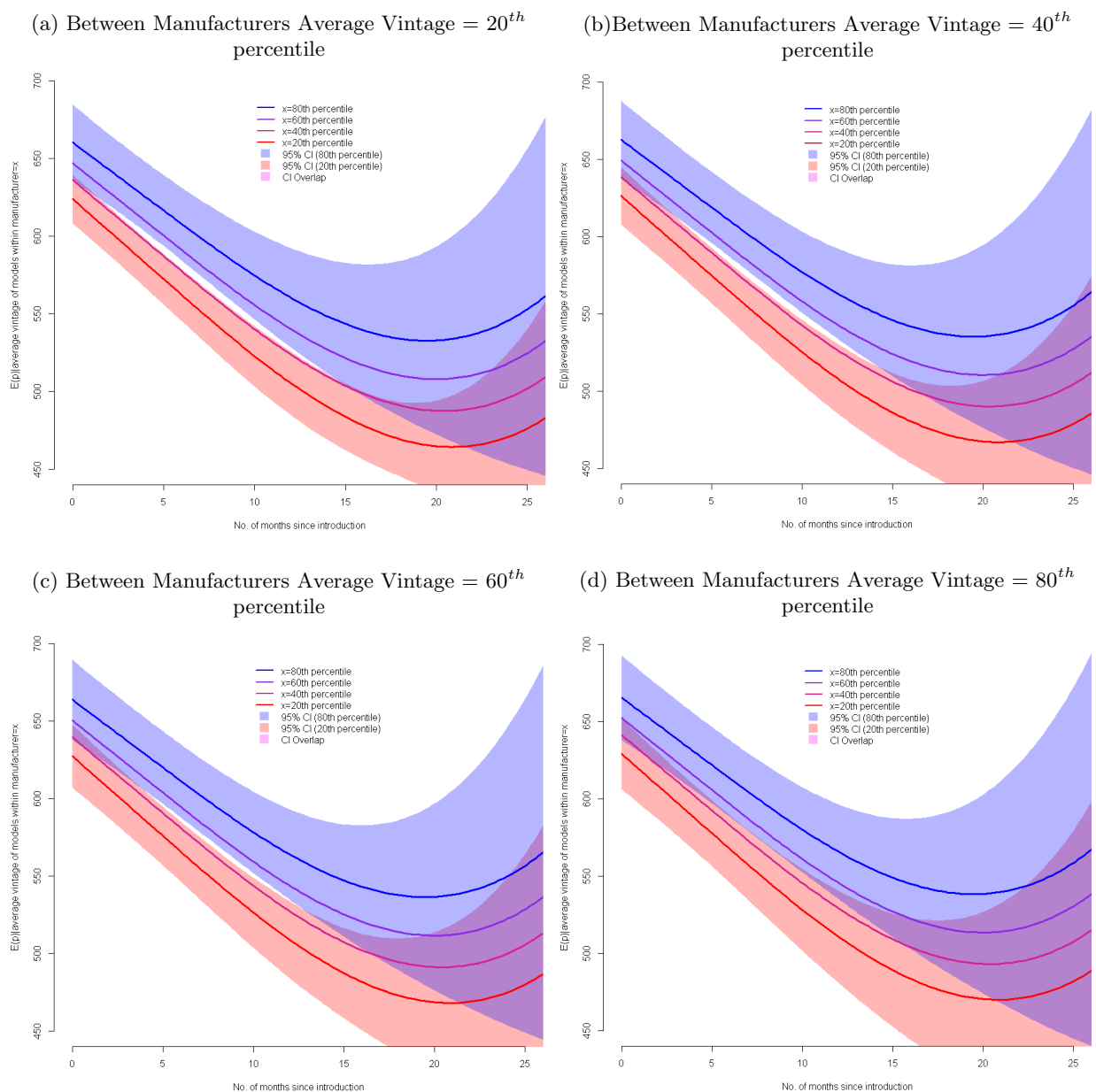
Figure H.7: LIFE CYCLE PRICING OF CLOTHES WASHERS
UNDER DIFFERENT BETWEEN-BRANDS AVERAGE VINTAGE



The figure shows that trend in the predicted price of a representative clothes washer using equation 15 during its first two years. We estimate equation 15 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.

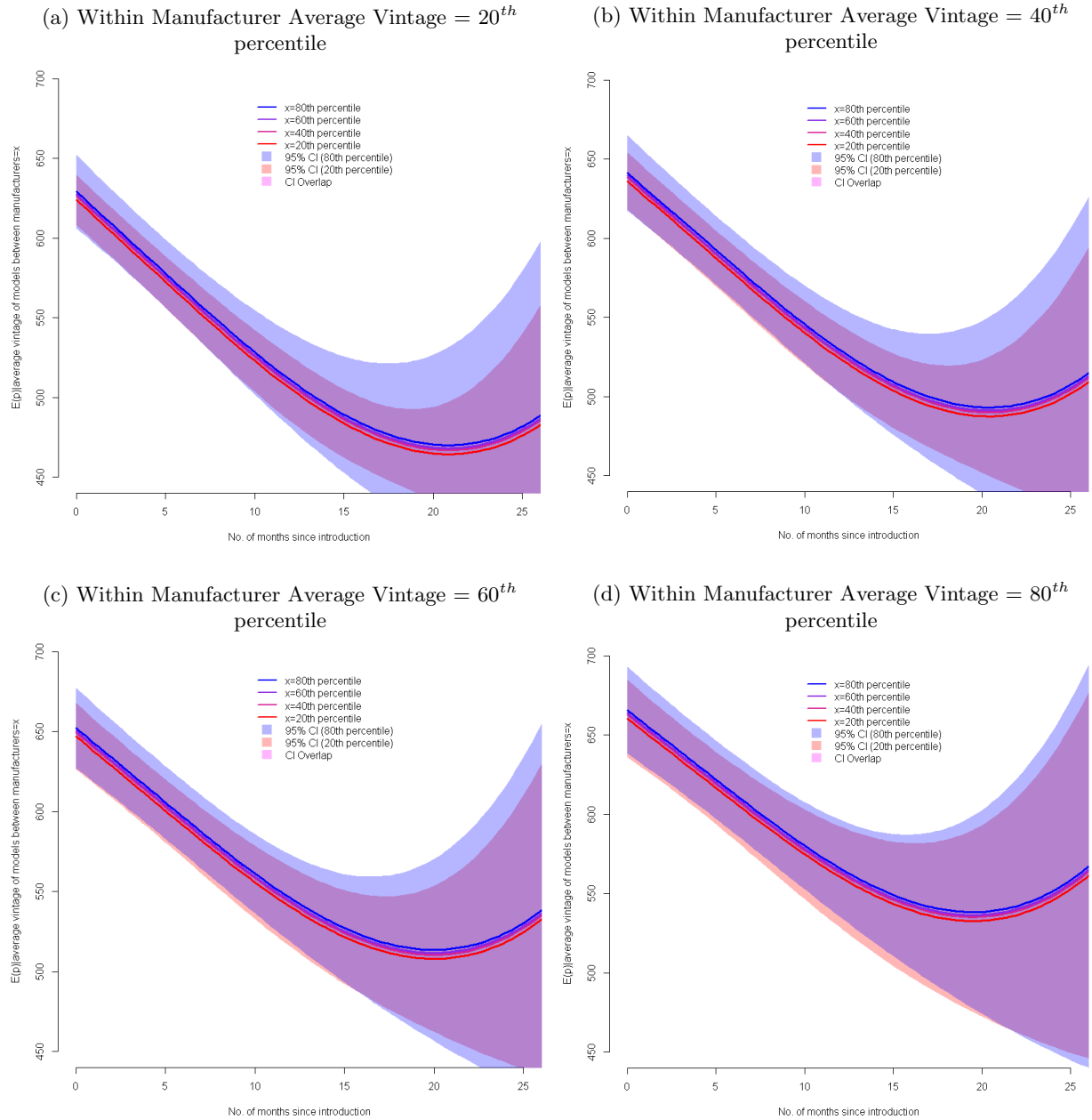
Figure H.8: LIFE CYCLE PRICING OF CLOTHES WASHERS
 UNDER DIFFERENT WITHIN-MANUFACTURER AVERAGE VINTAGE



The figure shows that trend in the predicted price of a representative clothes washer using equation 15 during its first two years. We estimate equation 15 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 H.9: LIFE CYCLE PRICING OF CLOTHES WASHERS
 UNDER DIFFERENT BETWEEN-MANUFACTURERS AVERAGE VINTAGE



The figure shows that trend in the predicted price of a representative clothes washer using equation 15 during its first two years. We estimate equation 15 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 I Within and Between Brands Competition and Price Trends for Clothes Dryers, Room Airconditioner and Refrigerators

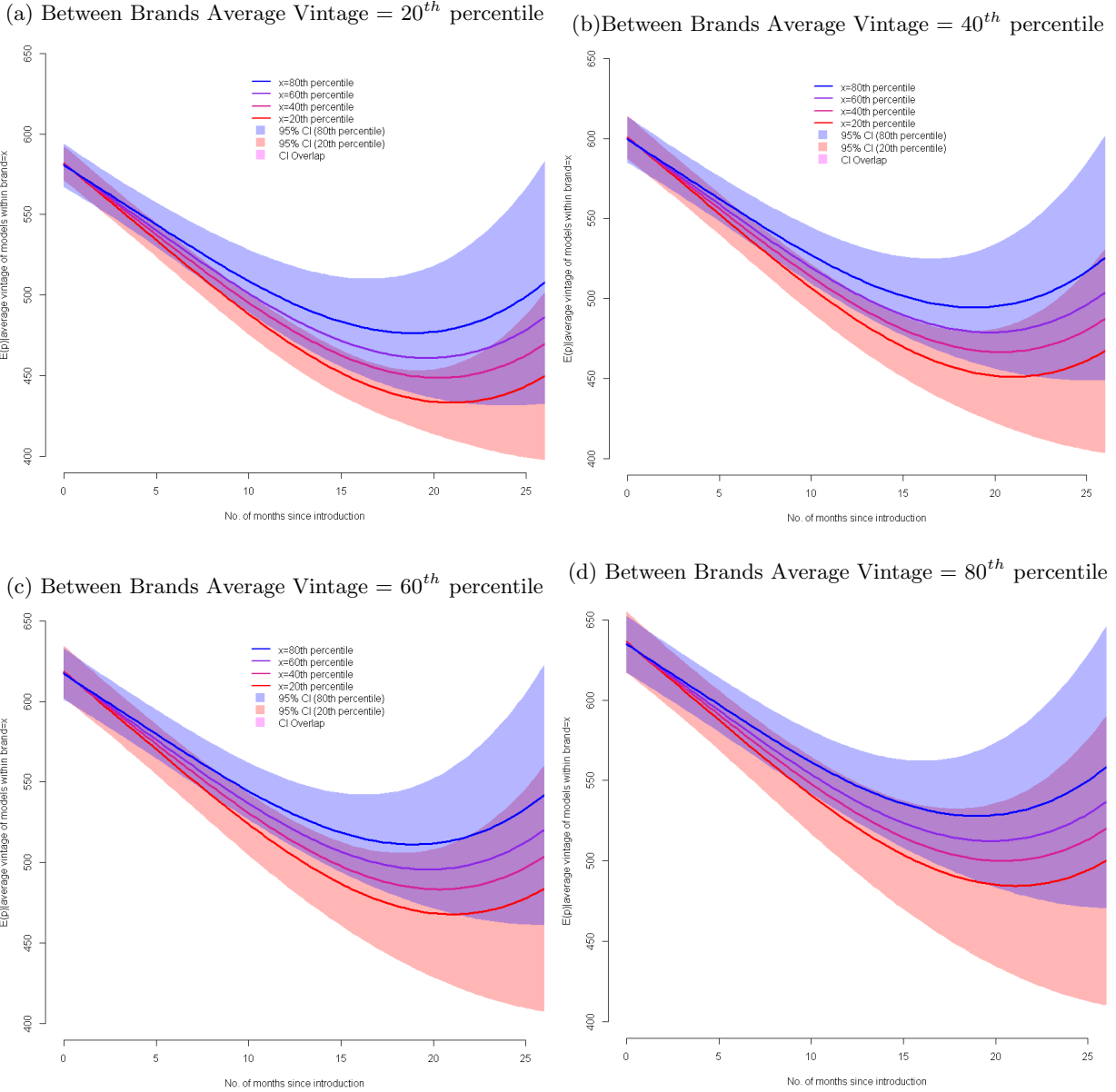
To see if cannibalism is unique to the appliance that had more stringent energy efficiency standards over the sample period (i.e. clothes washer), we use refrigerator, room AC and clothes dryer as counterfactuals. None of these appliances had adopted or implemented a simultaneous ME and ES certification change during the study period, although refrigerators had 2004 and 2007 ES policy changes. This section plots predicted price using estimates from equation 15 for these appliances.

I.A Clothes Dryers

We use the estimates from equation 15 to predict the price trend of typical clothes dryer holding average vintage of models within brands constant. Figure I.10 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 I.11 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 I.12 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 I.13 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).

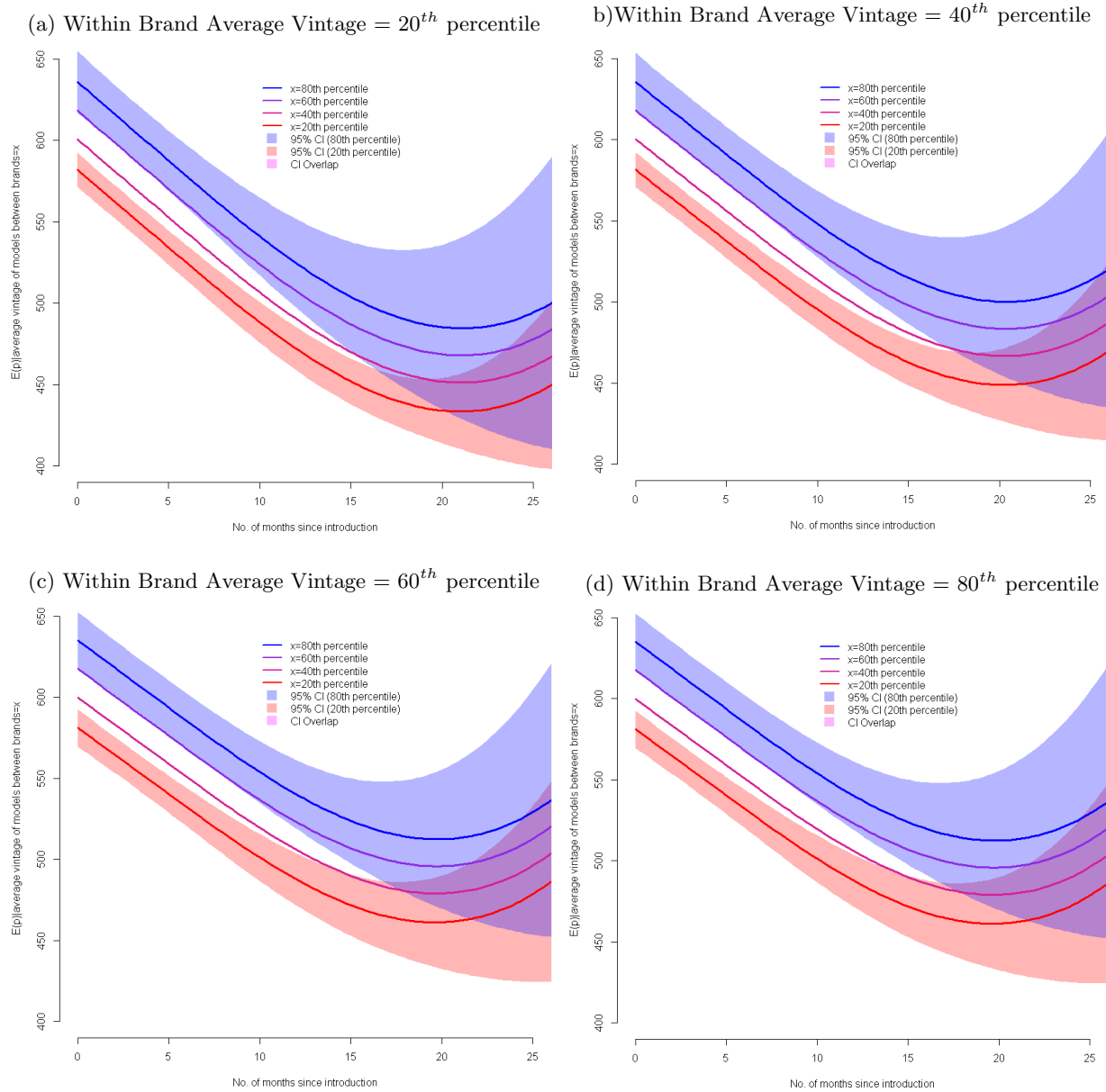
Figure I.10: LIFE CYCLE PRICING OF CLOTHES DRYERS UNDER DIFFERENT WITHIN-BRAND AVERAGE VINTAGE



The figure shows the trend in the predicted price of a representative clothes dryer using equation 15 during its first two years. We estimate equation 15 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.

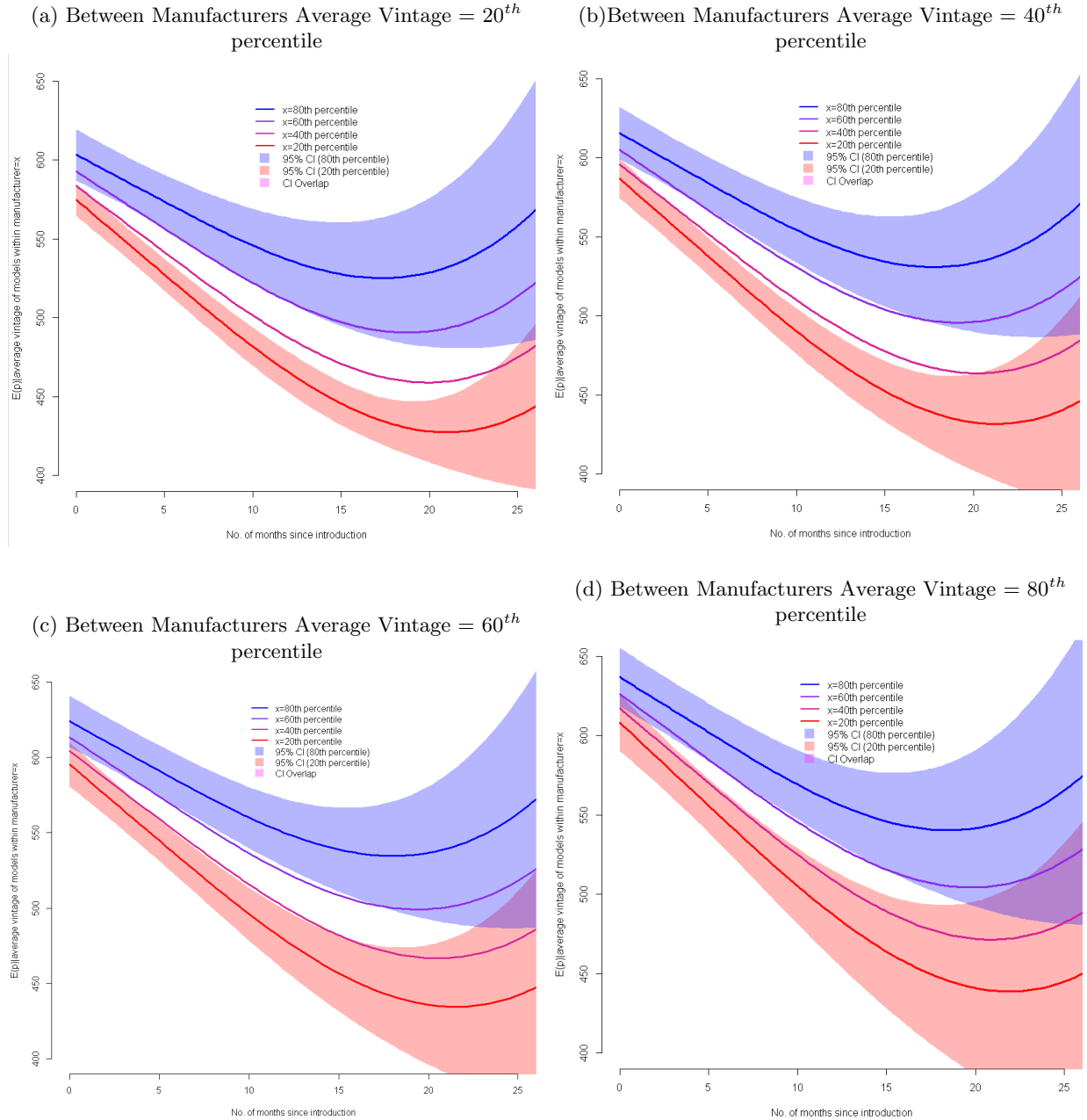
Figure I.11: LIFE CYCLE PRICING OF CLOTHES DRYERS UNDER DIFFERENT BETWEEN-BRANDS AVERAGE VINTAGE



The figure shows the trend in the predicted price of a representative clothes dryer using equation 15 during its first two years. We estimate equation 15 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 and 80th 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 and 80th percentile correspond to 10.12, 12.40, 14.54, and 16.67, respectively.

Source: Authors' calculations.

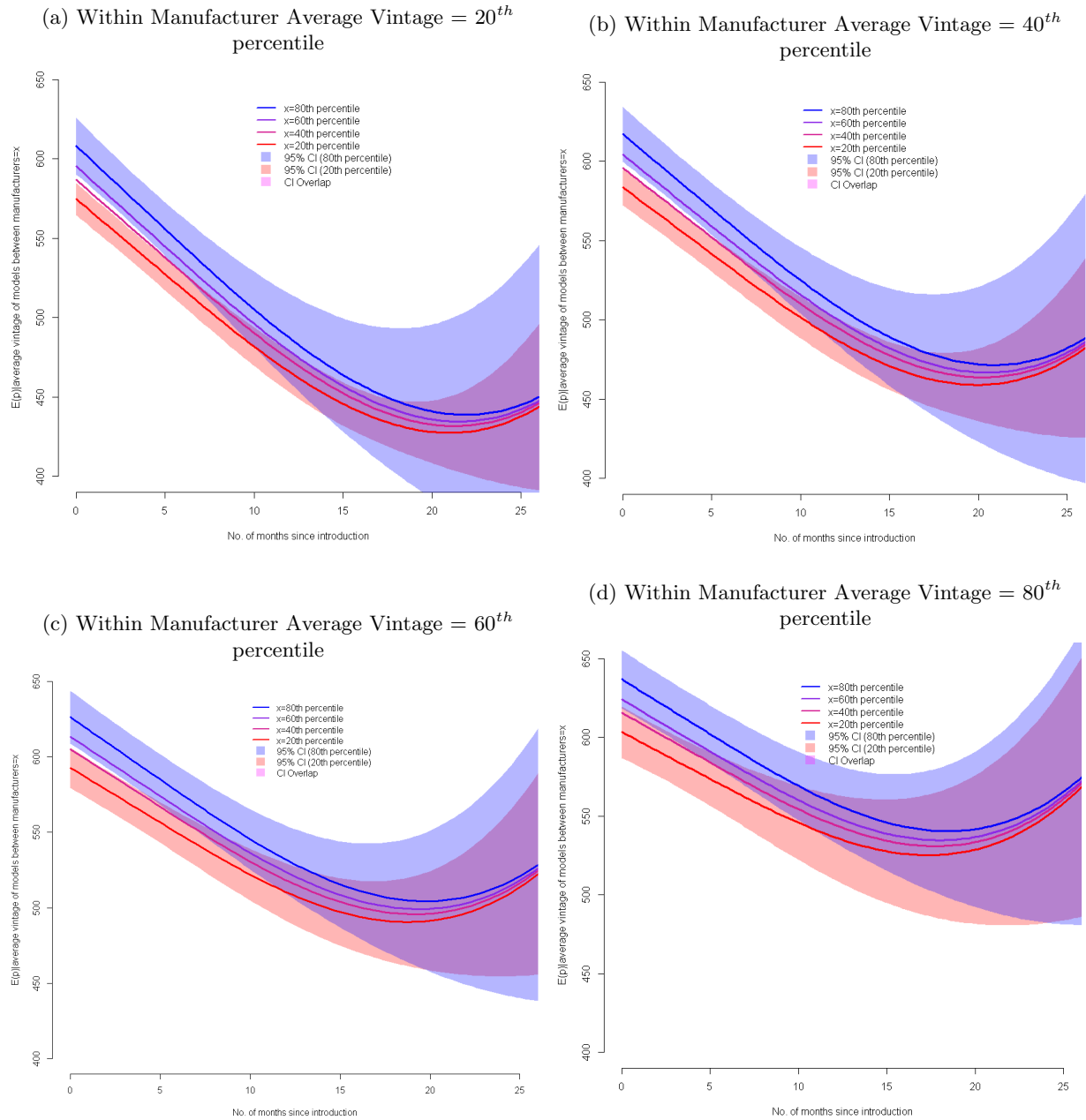
Figure I.12: LIFE CYCLE PRICING OF CLOTHES DRYERS UNDER DIFFERENT WITHIN-MANUFACTURER AVERAGE VINTAGE



The figure shows the trend in the predicted price of a representative clothes dryer using equation 15 during its first two years. We estimate equation 15 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 I.13: LIFE CYCLE PRICING OF CLOTHES DRYERS UNDER DIFFERENT BETWEEN-MANUFACTURERS AVERAGE VINTAGE



The figure shows the trend in the predicted price of a representative clothes dryer using equation 15 during its first two years. We estimate equation 15 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.

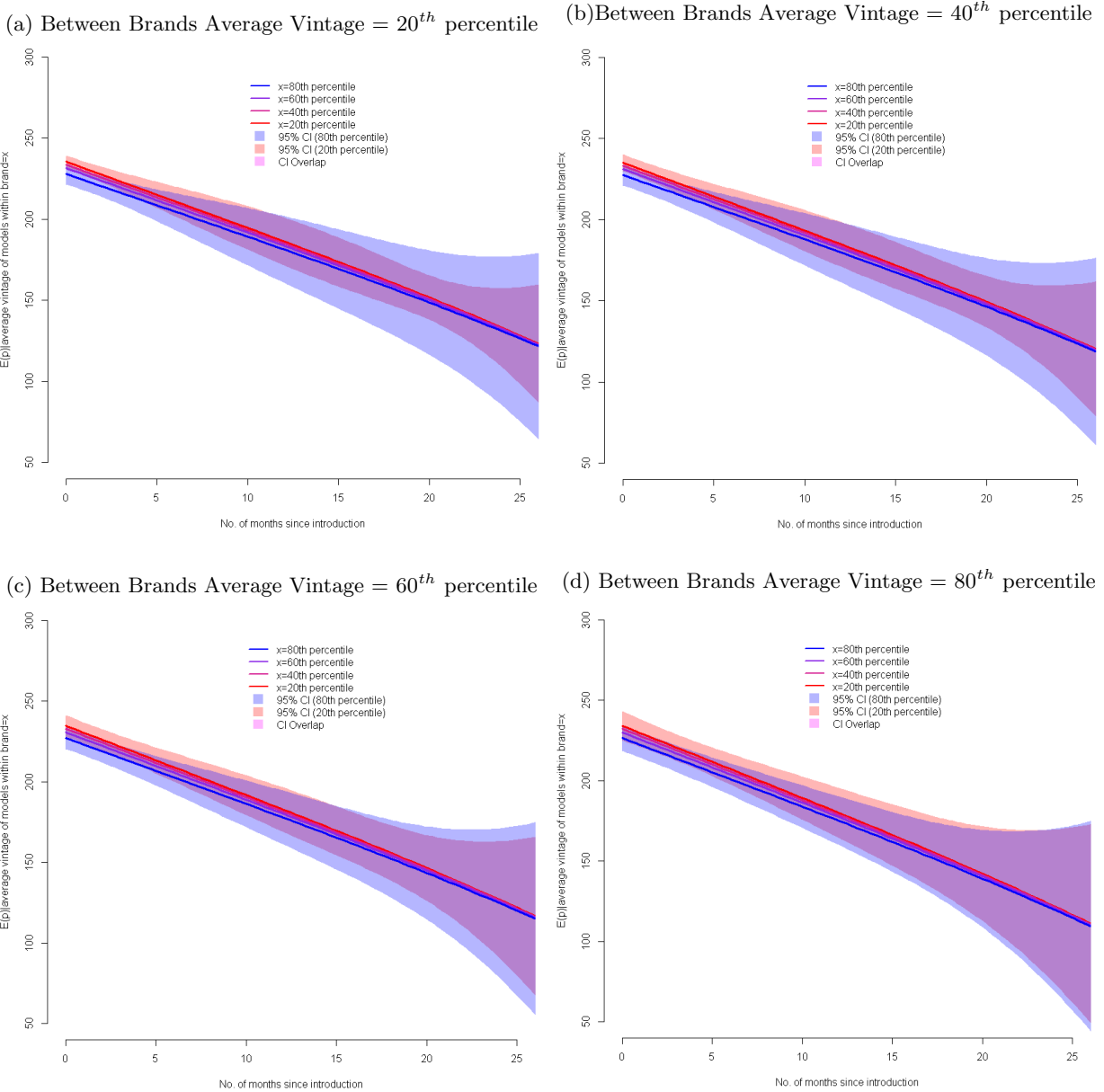
Source: Authors' calculations.

I.B Room Airconditioners

We use the estimates from equation 15 to predict the price trend of typical room AC holding average vintage of models within a brand constant. Figure I.14 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 I.15 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 I.16 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 I.17 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).

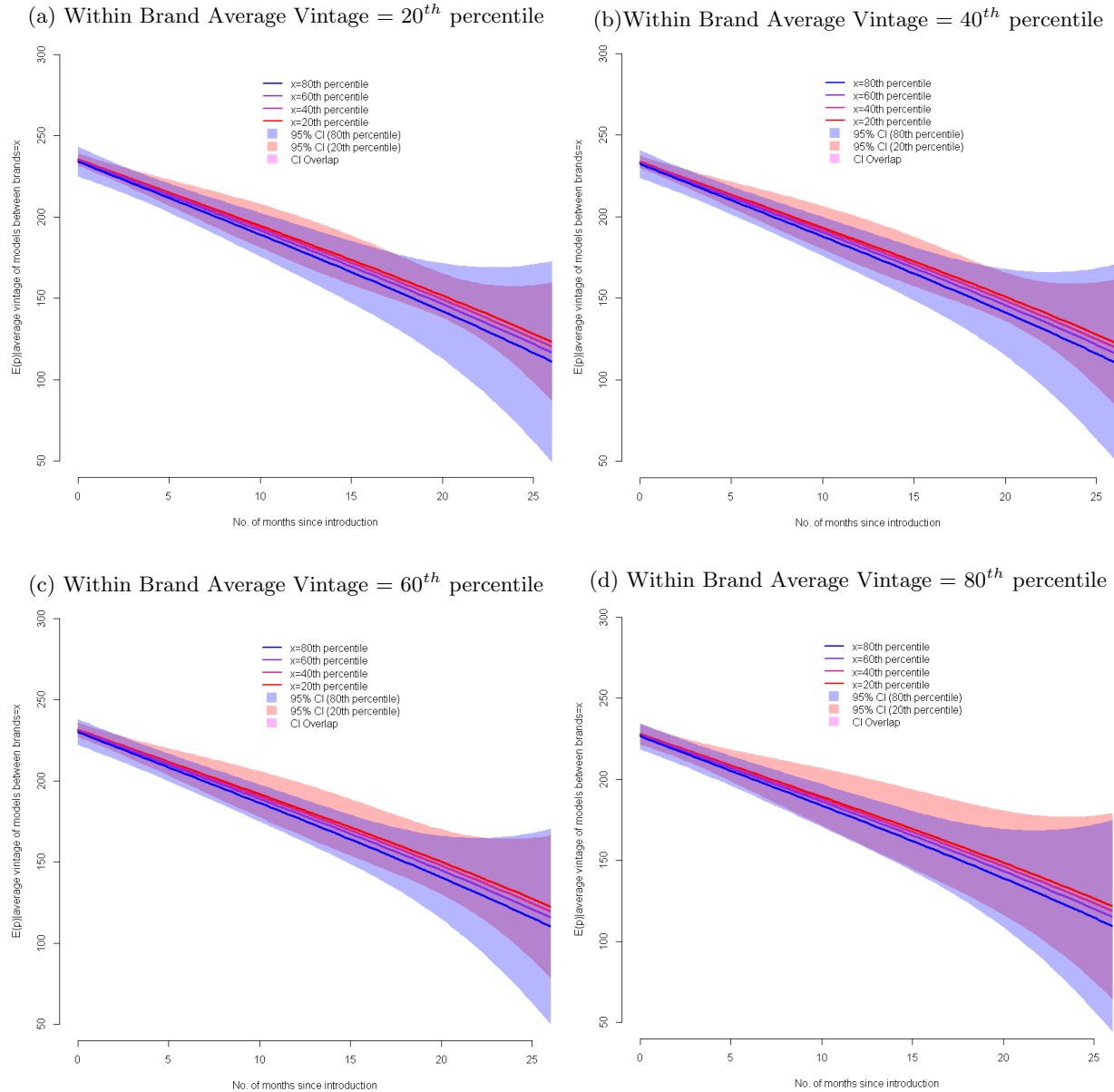
Figure I.14: LIFE CYCLE PRICING OF ROOM ACs UNDER DIFFERENT WITHIN-BRAND AVERAGE VINTAGE



The figure shows the trend in the predicted price of a representative room AC using equation 15 during its first two years. We estimate equation 15 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.

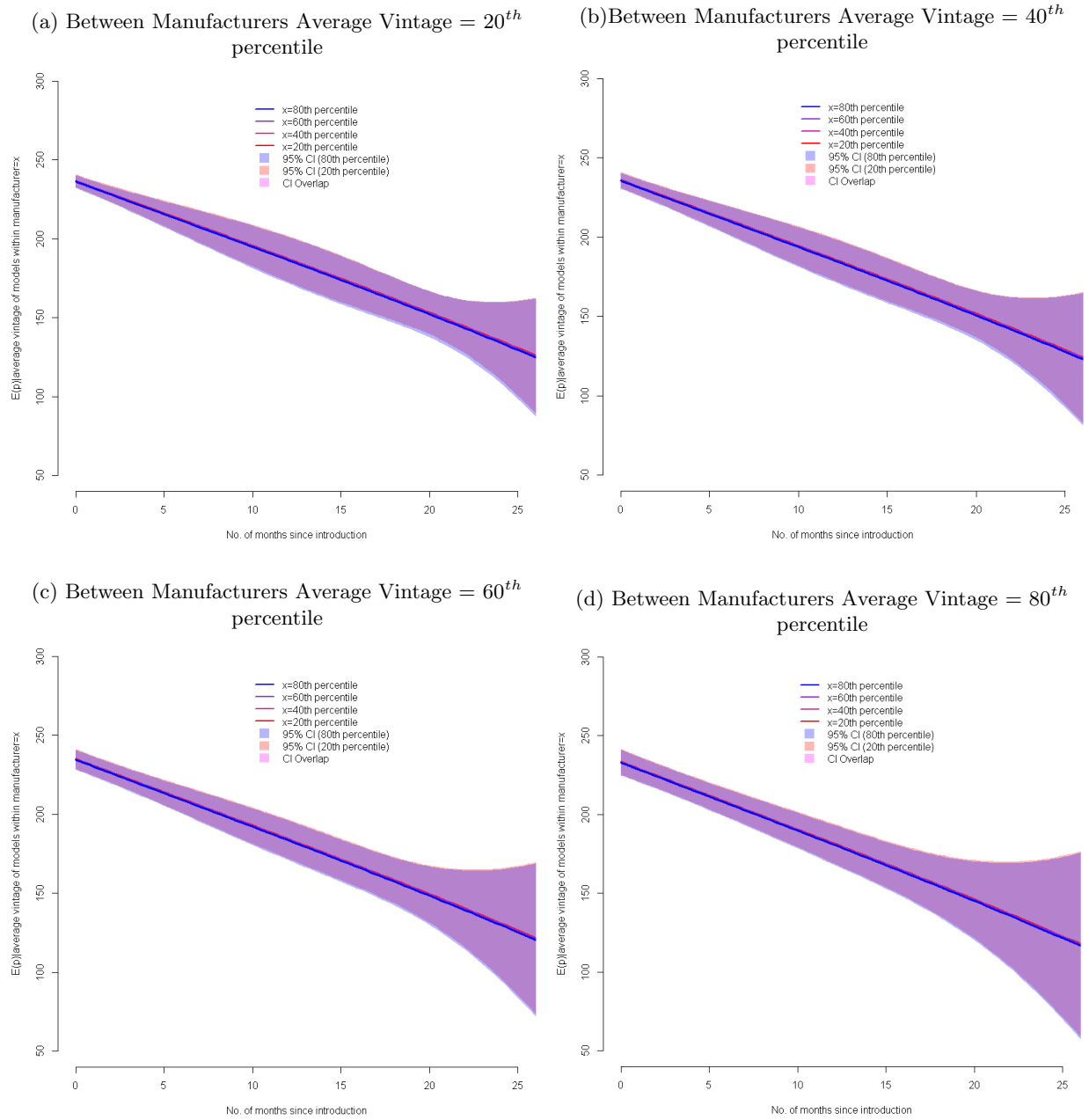
Figure I.15: LIFE CYCLE PRICING OF ROOM ACs UNDER DIFFERENT BETWEEN-BRANDS AVERAGE VINTAGE



The figure shows the trend in the predicted price of a representative room AC using equation 15 during its first two years. We estimate equation 15 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.

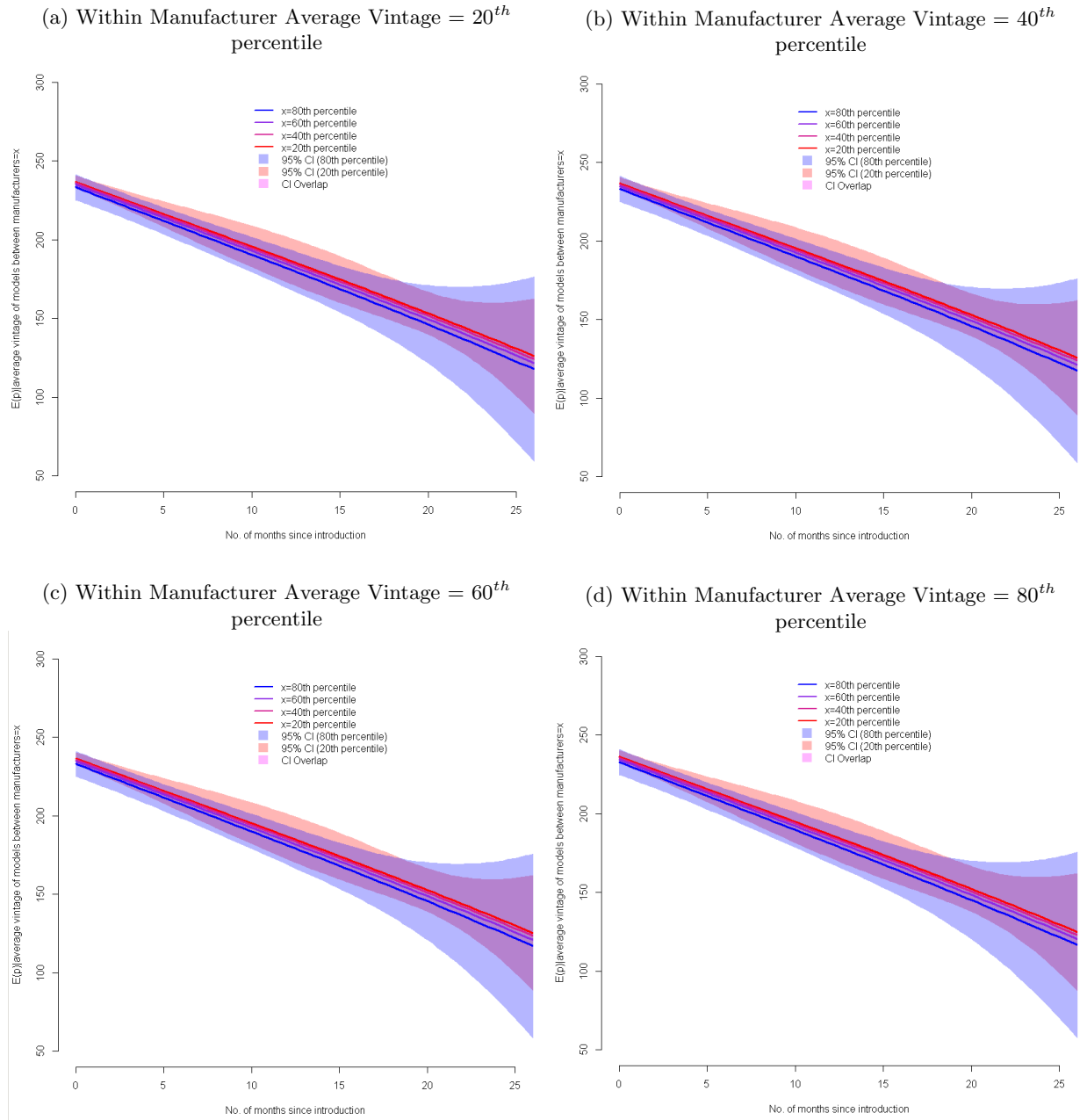
Figure I.16: LIFE CYCLE PRICING OF ROOM ACs UNDER DIFFERENT WITHIN-MANUFACTURER AVERAGE VINTAGE



The figure shows the trend in the predicted price of a representative room AC using equation 15 during its first two years. We estimate equation 15 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 I.17: LIFE CYCLE PRICING OF ROOM ACs UNDER DIFFERENT BETWEEN-MANUFACTURERS AVERAGE VINTAGE



The figure shows the trend in the predicted price of a representative room AC using equation 15 during its first two years. We estimate equation 15 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.

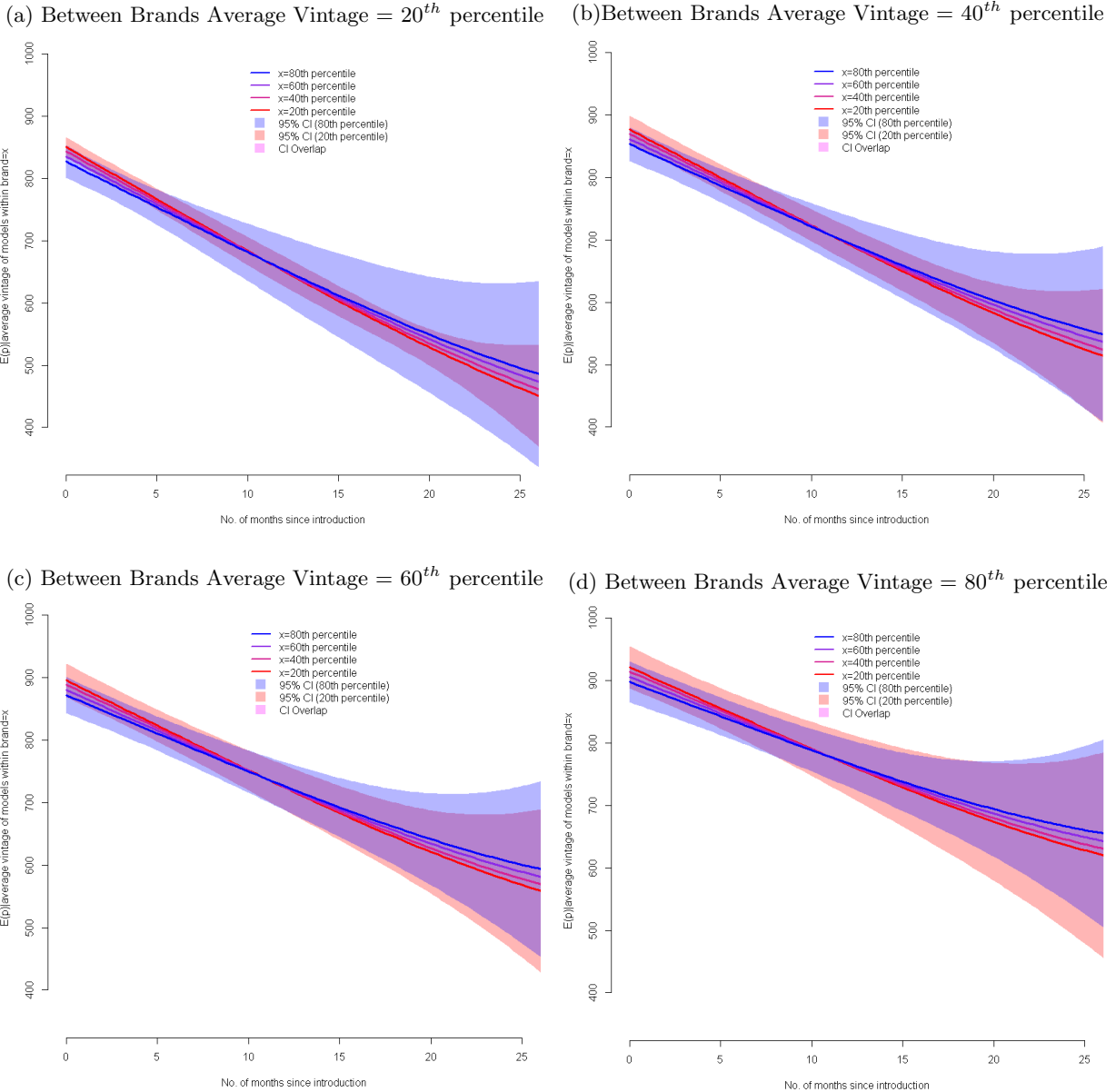
Source: Authors' calculations.

I.C Refrigerators

We use the estimates from equation 15 to predict the price trend of typical refrigerator holding average vintage of models within brands constant. Figure I.18 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 I.19 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 I.20 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 I.21 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).

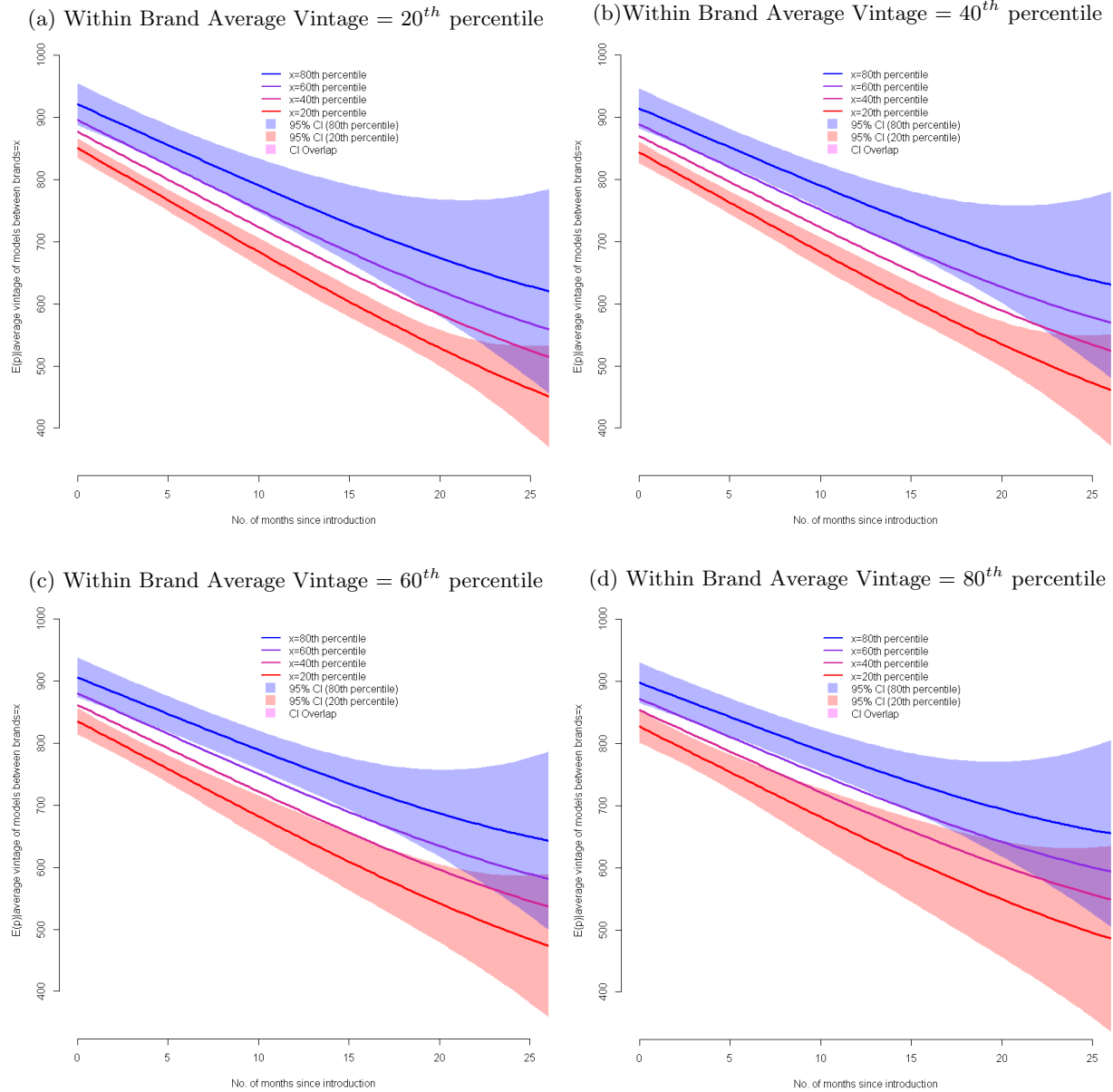
Figure I.18: LIFE CYCLE PRICING OF REFRIGERATORS UNDER DIFFERENT WITHIN-BRANDS AVERAGE VINTAGE



The figure shows the trend in the predicted price of a representative refrigerator using equation 15 during its first two years. We estimate equation 15 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.

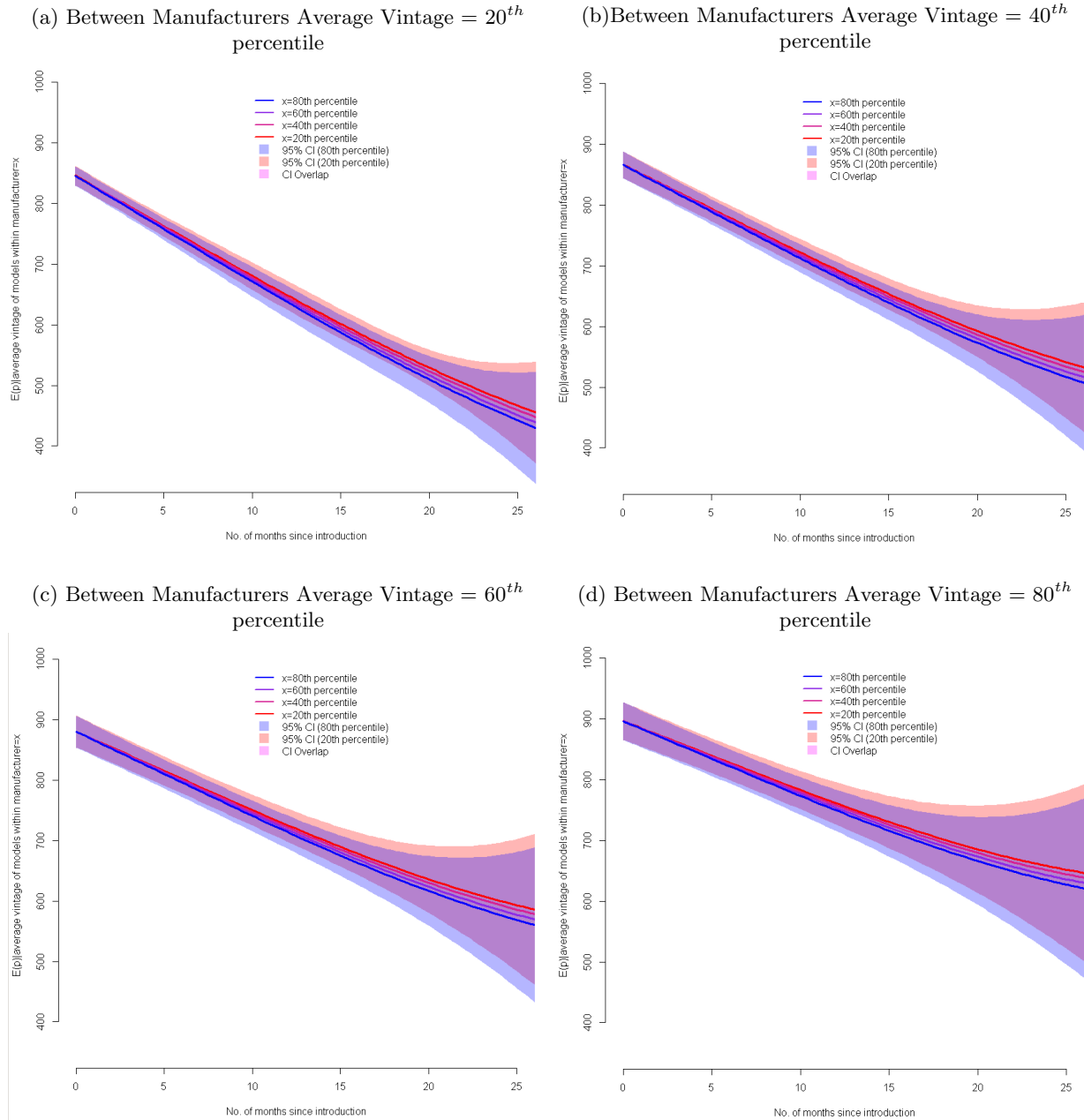
Figure I.19: LIFE CYCLE PRICING OF REFRIGERATORS UNDER DIFFERENT BETWEEN-BRANDS AVERAGE VINTAGE



The figure shows the trend in the predicted price of a representative refrigerator using equation 15 during its first two years. We estimate equation 15 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.

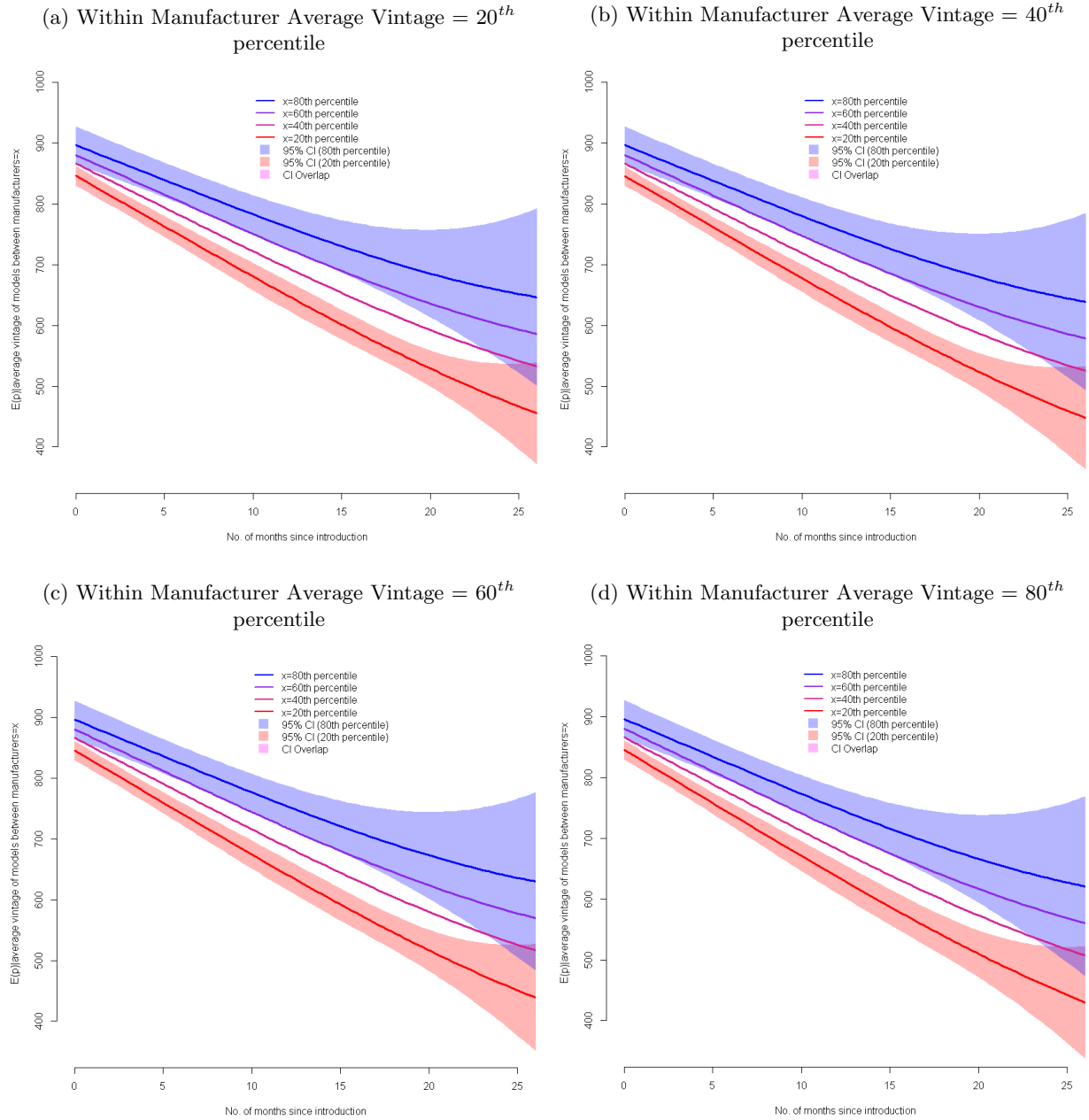
Figure I.20: LIFE CYCLE PRICING OF REFRIGERATORS UNDER DIFFERENT WITHIN-MANUFACTURER AVERAGE VINTAGE



The figure shows the trend in the predicted price of a representative refrigerator using equation 15 during its first two years. We estimate equation 15 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 I.21: LIFE CYCLE PRICING OF REFRIGERATORS UNDER DIFFERENT BETWEEN-MANUFACTURERS AVERAGE VINTAGE



The figure shows the trend in the predicted price of a representative refrigerator using equation 15 during its first two years. We estimate equation 15 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.